Essays in empirical asset pricing and international finance

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Essays in Empirical Asset Pricing and International Finance

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Introduction

This Ph.D. dissertation consists of three chapters. The first chapter provides a mispricing explanation for the risk-return relationship on days with and without macroeconomic news announcements. It demonstrates the importance of investor belief dispersion and short-selling constraints in shaping the security market line on those two types of days. The second chapter utilizes a large international sample and studies the firm and country characteristics that determine stock return exposures to periods of market stress. The third chapter use tick-by-tick data of benchmark stock index and government bond futures and identify and characterize occurrences of flights-to-safety at high frequency across 10 countries over the last 20 years.

The first chapter studies the relation between risk and returns on two different set of days. In particular, the relationship between market beta and expected returns is positive on days with pre-scheduled macroeconomic news announcements (MNAs), but negative on the other days. This paper shows evidence that stock price underreaction to MNAs explains these phenomena. First, I use high-frequency S&P 500 futures data to identify positive (good) and negative (bad) news from macro announcements. Stocks with low sensitivities to bad macro news perform relatively well on announcement days and poorly on the following non-announcement days. Moreover, the under-performance of low sensitivity stocks is most pronounced when investor disagreement is high and short-selling constraints are binding. Subsequently, I show that the relation between market betas and returns on announcement (non-announcement) days is particularly positive (negative) among stocks with low sensitivities to bad macro news. The results are consistent with stocks, especially those with high market betas, underreact to bad news on MNA days when high shorting costs prevent prices from reflecting pessimists' beliefs, and experience low returns on the following non-announcement days.

The second chapter uses a newly developed crisis indicator and firm-level data from nearly

40,000 stocks from 54 countries and searches for the firm and country characteristics that make stocks excessively exposed to stress periods. In a first step, we build a predictive model for firm betas in 'normal times' and identify their firm and country determinants. Using these predicted betas, we calculate abnormal returns and define unexplained increases in factor loadings and residual correlations during crisis periods as indicative of contagion. We develop and test several hypotheses that link contagion exposures to (a combination of) firm and country fundamentals.

The third chapter studies flight-to-safety (FTS). Using tick-by-tick data of benchmark stock index and government bond futures, we identify and characterize occurrences of flights-to-safety at high frequency across 10 countries over the last 20 years. We define FTS events as the 5-minute intervals during which equities crash while bond prices surge. During a typical 5-minute FTS interval, equities drop with 0.6% to 0.8%, while bonds increase with 0.18% to 0.25%. FTS events tend to be short-lived and associated with high trading volume. While realized volatility surges during FTS, it is not particularly high before or after FTS intervals. We document that many FTS are triggered by US macroeconomic announcements and provide first evidence on how FTS transmit globally.

Contents

Chapter 1

Underreaction to Macro Announcements and the Boom and Bust of CAPM

1 Introduction

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) implies that stocks with higher market betas should deliver higher expected returns. However, empirical studies have presented an abundance of evidence suggesting a flat or even downward-sloping security market line (see Black et al. (1972), Baker et al. (2011), and Frazzini and Pedersen (2014)). Recently, Savor and Wilson (2014) document a significantly positive relationship between market beta and average returns on days when pre-scheduled macroeconomic news announcements (MNAs) are released. However, the positive slope of the security market line on MNA days and its overall flatness mechanically implies a negative slope on non-MNA days. This paper confirms the negative relationship between market beta and non-MNA day returns using a comprehensive set of MNAs. More importantly, I present an explanation for the positive relation on MNA days but negative relation on non-MNA days: underreaction to negative macroeconomic news.

I first document strong and robust evidence of firm-level stock price underreaction to negative macro news. To quantify the news, I use five-minute returns on E-mini S&P 500 futures immediately after the release time of announcements. I distinguish between good and bad news based on the sign of returns: the news is defined to be bad (good) when the announcement return is negative (positive). I show that firms with tight short-selling constraints and high investor disagreement have low sensitivities to bad macro news. In other words, these firms perform relatively well on days when the market plunges following a macro announcement. Moreover, stocks less sensitive to bad news experience much lower returns in the following month than high-sensitivity ones, especially on days without announcements. The relation is particularly strong for stocks with high investor disagreement and high short-selling constraints.

Following the argument of Miller (1977), the results are consistent with underreaction to bad announcement news due to tight short-selling constraints and investor disagreement on firm value. Specifically, following a bad announcement, stocks with high costs of short-selling will be slower in incorporating the negative macro news, especially when investors have diverse beliefs on how the firm should respond. The combination of short-sales constraints and disagreement leads to over-valuation, or under-reaction to the bad news, as stock prices reflect more of the beliefs of optimistic investors. Therefore, these stocks will have low sensitivities to bad macro news and experience lower returns in the future as the mispricing is gradually corrected.

The findings have strong implications for the relationship between market beta and returns on both MNA and non-MNA days. Since stocks with high market betas tend to have high exposures to macroeconomic risk, they should be more affected by bad macro news. Meanwhile, investors of high-beta stocks may also have high disagreement, and underreaction to bad news will be more pervasive among those stocks. Thus, low sensitivities to bad macro news should lead to high returns on MNA days and low returns on the non-MNA days particularly for high-beta stocks. I therefore hypothesize that among stocks with low sensitivities to bad macro news, the relation between beta and non-MNA day returns is the most negative, and the relation between beta and MNA day returns is the most positive.

This paper confirms the hypothesis by first showing that, consistent with Diether et al. (2002) and Hong and Sraer (2016), high-beta stocks tend to observe high investor disagreement. More importantly, stocks with low sensitivity to bad news have the most negative relationship between market beta and non-MNA day returns. However, the relation is much more flattened among stocks with high sensitivities, with the magnitude reduced by 50%. Meanwhile, the relation between market beta and returns on MNA days is the most positive among stocks with low sensitivities to bad news, and the magnitude is also lower by around 50% for stocks with high sensitivities. Therefore, underreaction to bad news on MNA days plays an important role in explaining the beta-return relation on MNA days and non-MNA days. The results are robust to controlling for a battery of firm characteristics and alternative estimations of the sensitivity.

My empirical analysis begins with identifying and quantifying macro news. I collect the pre-scheduled release dates and times of a comprehensive set of 14 macro news announcements which trigger significant stock market reactions (see Kurov et al. (2017) and Law et al. (2018)). Many of the announcements are made at 8:30 a.m. Eastern Time when the US stock market is still closed. I therefore use E-mini S&P 500 futures, which trade almost around the clock. I use five-minute returns immediately after announcements to measure market reaction to the news. The tight window isolates the impact of MNAs from other significant events which may influence stock prices. Based on the sign of returns, I split news into good (positive returns) and bad (negative returns) macro news. Furthermore, I compare the five-minute announcement returns with a trailing jump-robust volatility of returns over the past five trading days. Only the returns with an absolute value higher than one unit of volatility are included in my further analysis, although my results are robust to alternative thresholds.

To measure underreaction to negative news, I then estimate firm-level sensitivities to bad announcement returns. At the end of each month, I regress daily stock returns on good and bad announcement returns over the past 24 months, controlling for the market factor. I document a wide dispersion of both good and bad MNA sensitivities. Sorting stocks into deciles based on the bad MNA sensitivity, I find a statistically and economically significant relationship between the bad MNA sensitivity and future returns. On the days without MNAs, the highest decile portfolio outperforms the lowest decile portfolio by 0.89% per month, with a t-stat of 2.74. The difference mainly comes from the increase in returns from -1.01% for the lowest decile portfolio to -0.17% for the fifth decile portfolio. The top five deciles, however, have average returns close to zero. On days with MNAs, average returns across all deciles are close to 0.7% per month, except for the bottom and top decile with over 1% per month. At the same time, sorting stocks into deciles based on good MNA sensitivities does not generate much spread in monthly returns on both MNA days and non-MNA days.

To test the robustness of the relation to well-known firm characteristics that predict cross-sectional stock returns, I next perform stock-level Fama-Macbeth regressions. The coefficients on the bad MNA sensitivity for full month returns and non-MNA day returns are positive and significant after controlling for firm and risk characteristics including size, book-to-market, illiquidity, and idiosyncratic volatility. On MNA days, however, there is no significant explanatory power of the bad MNA sensitivity. Moreover, I expect that underreaction will be more dominant for stocks with negative sensitivities to bad macro news. The stocks in the long leg could underreact, but it should contain the least degree of underreaction. This hypothesis is confirmed as I find that the positive relation on non-MNA days concentrates on stocks with lower-than-median bad MNA sensitivities.

I next provide evidence that the underreaction is caused by investor disagreement and short-selling constraints by exploiting cross-sectional variations in the two variables. I posit that short-sales constraints are tight for stocks with low residual institutional ownership following Nagel (2005), Asquith et al. (2005), Boehme et al. (2006), and Weber (2018). For disagreement on how stocks should react to macro news, I use analysts forecast dispersion on earnings, turnover on MNA days, and the standard error of estimated market beta following Armstrong et al. (2013), Diether et al. (2002) and Boehme et al. (2006). Arguably, a larger standard error suggests a higher uncertainty on the firm's exposure to the aggregate economy, and potentially higher investor disagreement on the exposure. I first show that stocks with high short-selling constraints and high investor disagreement tend to have low sensitivities to bad news. Second, I find that stocks with low sensitivities to bad macro news experience low returns especially when they have low institutional ownership and high analysts' forecast dispersion, high turnover on MNA days, or high standard error of estimated market beta. Both tests lend support to the hypothesis that underreaction is caused by short-selling constraints preventing stock prices from reflecting the views of pessimistic investors.

Finally, I examine how stock price underreaction to bad macro news explains the relationship between market beta and expected returns on MNA days and non-MNA days. First, firm-level regressions show that high-disagreement stocks also tend to have high market betas. This result suggests that underreaction is more pervasive among high-beta stocks. To show the role underreaction plays in the beta-return relation, I then conduct portfolio double-sorting where stocks are first sorted into quintiles based on bad MNA sensitivities and subsequently into quintiles based on market beta. The slope of the security market line on non-MNA days is the most negative for stocks within the lowest quintile of bad news sensitivities, which are the stocks that are most likely to underreact to negative macro news. On the other hand, among stocks within the highest quintile of sensitivity to the bad news, which are the stocks that are least likely to underreact, the security market line is only insignificantly negative, with the magnitude shrunk by 50%. On MNA days, the relation between returns and market betas is the most positive among stocks with low sensitivity to the bad news. Among high sensitivity stocks, the magnitude of the relation is also reduced by around 50%. I also show that the result is robust to a battery of firm characteristic and alternative estimates of bad MNA sensitivity.

A risk-based explanation for the positive relationship between the bad MNA sensitivity and returns on non-MNA days is faced with many challenges. First, the bad MNA sensitivity may serve as a direct measure of MNA risk for individual stocks. However, it is difficult to explain why investors, knowing the dates of pre-scheduled announcements, ask for a premium on MNA risk during days without announcements instead of MNA days. Second, my analysis shows that the bad MNA sensitivity is insignificantly related to a list of well-known risk characteristics, such as downside risk from Ang et al. (2006a). Moreover, a risk-based explanation is inconsistent with the observation that, among stocks with higher-than-median bad MNA sensitivity, investors are not compensated for bearing more risk by higher returns on non-MNA days.

The paper is mostly related to the recent literature on stock returns on macroeconomic news announcement days and non-announcement days. Savor and Wilson (2013) document high stock market returns and Sharpe ratios on MNA days. Savor and Wilson (2014) show that the relation between market beta and average returns is positive on MNA days but negative on non-MNA days. Ai and Bansal (2018) and Wachter and Zhu (2018) show that under certain assumptions about utility function or consumption process, investors ask for announcement premium around macro news announcements. Savor and Wilson (2014) state in their conclusion that "It remains to supply the fundamental economic explanation as to why our findings hold". Wachter and Zhu (2018) present a model with rare events that explains the positive relation between market beta and returns on MNA days. However, the model also results in a slightly upward-sloping, instead of downward-sloping, security market line on non-MNA days. In contrast, my study confirms the negative slope of the security market line on non-MNA days and provides evidence for an explanation based on underreaction to macroeconomic announcements.

This work also contributes to the literature investigating the potential factors behind the flat or downward-sloping security market line. Cohen et al. (2005) examine the effect of inflation on the security market line. Huang et al. (2016) study the impact of speculative capital committed to betting against beta. Antoniou et al. (2015) examine the relation between the pricing of beta and variations in investor sentiment. Jylhä (2018) shows that tighter leverage constraints result in a flatter relation between beta and expected returns. Hong and Sraer (2016) show that disagreement on aggregate variables affects the slope of market security line as higher-beta stocks are more likely to be overvalued in the presence of limits to arbitrage and disagreement about aggregate growth. Although they do not model public information announcements, their model should lead to lower (higher) returns on high-beta stocks during MNA (non-MNA) days. The reason is that the overvaluation of high-beta stocks should occur on non-MNA days and be corrected on MNA days, as announcements will reduce disagreement on aggregate variables. In contrast, my paper focuses on firm-level disagreement and shows evidence that overvaluation occurs on announcement days in the form of underreaction to bad news.

This study also relates to the literature on the impact of MNA surprises on asset prices. McQueen and Roley (1993), Boyd et al. (2005), Andersen et al. (2007), and Law et al. (2018) show that there is a strong relationship between stock prices and news which varies across the business cycle. Gilbert et al. (2017) show that timeliness and relation to economic fundamentals explain the variation in the response of U.S. Treasury yields to macroeconomic news announcements. De Goeij et al. (2016) find fixed results for the pricing of macroeconomic announcements in the cross-section of stock returns. A major difference of this paper is the usage of five-minute announcement returns to measure MNA shocks rather than the difference between surveyed professional forecast and actual values. Therefore, the MNA shocks in this study measure the "surprise" from the perspective of investors revealed in prices. Similarly, Gürkaynak et al. (2005) and Gertler and Karadi (2015) use 30-minute returns on federal fund futures to measure monetary policy surprises. Furthermore, my firm-level analysis contributes to this literature by showing evidence that stocks underreact to bad MNA news although the aggregate market immediately respond to announcements.

This study also contributes to the empirical literature on mispricing due to investor disagreement and short-sales constraints. Diether et al. (2002) find that stocks with higher dispersion in analysts' earnings forecasts earn lower returns in the future. Asquith et al. (2005) consider institutional ownership as a proxy for short-selling supply and find under-performance of constrained stocks on an equal-weight basis. Boehme et al. (2006) find evidence of significant overvaluation for stocks that have both short-selling constraints and investor disagreement. They emphasize that either condition alone is not sufficient to produce overpricing. Studies such as Nagel (2005), Phalippou (2008), Hirshleifer et al. (2011), and Weber (2018) use institutional ownership as a proxy for the ease of short-selling and show that short-sale constraints explain many cross-sectional return anomalies. This paper adds to the literature by showing evidence that a significant amount of overpricing occurs on days with MNAs.

2 Data and Methodology

2.1 Macroeconomic news announcements

Following Andersen et al. (2007), Kurov et al. (2017) and Law et al. (2018), I focus on 14 macroeconomic news announcements, all listed in Table 1. I do not include announcements of PPI, GDP final, housing sales, government budgets, trade balance, personal income, leading indicators and factory orders, as surprises of these announcements are not followed by significant stock market movements (Table B3 in Kurov et al. (2017) and Table 1 in Law et al. (2018)). The dates and times of announcements are mainly obtained from the related agency websites. For those of which the release dates are not available from websites, I use Factiva to identify historical release dates. On average, there are 11 trading days with one or more macro announcements during a month, and 10 trading days without announcement. According to Kurov et al. (2017), two of these announcements, ISM Manufacturing Index and ISM Non-Manufacturing Index, have pre-announcement price drift in the same direction of the announcement surprise, indicating information leakage before announcement. However, both of the announcements are released at 10:00 a.m, so an alternative explanation could be that informed investors trade on their private information after the stock market is open on 9:30 a.m. for liquidity and transaction cost issues. I also include FOMC announcements for the main results. However, Lucca and Moench (2015) report unconditional excess returns in equity index futures during 24 hours prior to the FOMC announcements. Ai and Bansal (2018) also point out that most of the premiums for FOMC announcements are realized in several hours prior to the announcements. It seems that, instead of receiving information on announcement time, investors obtain signals and update their beliefs on monetary policy before FOMC announcements. Excluding FOMC announcements in the sample have little impact on the results of this paper.

2.2 High-Frequency data on E-mini S&P 500 futures

I obtain high-frequency data from Thomson Reuters Tick History for E-mini S&P 500 futures (ES). As investors of the equity index futures bear market-wide risk instead of firm-specific risk, the announcement returns measure the impact of announcements on the market. Each observation is time-stamped to the millisecond. I clean the data by dropping price observations that are higher (lower) than the daily high (low) price of futures from Datastream. I construct a new liquidity-maximum continuous series for futures using nearby contracts (closest to maturity) and the next contracts (second closest to maturity). In particular, I roll over from front-month contract to next contract on the day when there are more trades in the next contract than the other. Prices are sampled every five minutes from 7:55 EST until 16:00 EST, using the last recorded trading price within each five-minute interval, e.g., 7:55:00:000 to 7:59:59:999. The choice of frequency strikes a balance between the need of tight window around announcements and and the need to avoid microstructure noise. There are at most 97 price observations during a day. A trading day is dropped if it has fewer than 80 sampled price observations. I obtain five-minute returns as the difference between two adjacent logged prices. If there is no price in a five-minute interval, the return is set to zero. Following this procedure, there are 96 five-minute returns for each trading day. Announcement returns are defined as the five-minute returns immediately following macroeconomic news announcements. For example, if an announcement is made on 8:30 EST, then the announcement return is the log difference in price between 8:29:999 EST and 8:34:999 EST.

Figure 1 further motivates the choice of window size of five minutes. I plot the standard deviation of one-minute returns over each one-minute interval around announcements. The figure shows that the standard deviation increases immediately after the announcements and gradually decreases to the pre-announcement level over the following five minutes. The pattern indicates that announcement surprises are mostly incorporated into futures price within five minutes. Therefore, five-minute returns suit the need to capture market reaction to macro announcements.

An alternative measure is the difference between announcement realizations and their forecast values from a survey of professionals (MNA surprises). However, announcement returns are more suitable in this paper for the following reasons. First, the same amount of surprise (the scaled difference between actual and forecast value) from different announcements have different market relevance. Returns on equity index futures provide a uniform measure which is comparable among MNAs. Second, big MNA surprises may not always have a substantial market impact. Announcement returns serve as a natural proxy for surprises of announcements from the perspective of investors. Third, good economic surprises (better-than-expected) are not necessarily good news to the stock market. Using returns allows me to have a clear separation of good and bad MNA shocks.

However, not all announcements necessarily convey unexpected and important information that will move the stock market. Following Jiang and Zhu (2017), I restrict my sample of announcement returns to those presumably dominated by information surprises. Specifically, I compare the announcement returns with volatility. Consider an MNA released on 8:30 E.T. on a given day. The return from 8:30 to 8:35 is denoted as r_j where j indexes five-minute intervals. I first estimate integrated variance over the past five days, or in total $K = 96 \times 5$ observations of five-minute returns, using the MedRV estimator from Andersen et al. (2012),

$$MedRV = \frac{\pi}{6-4\sqrt{3}+\pi} \times \frac{K}{K-2} \sum_{i=j-K+2}^{j-1} med(|r_i|, |r_{i-1}|, |r_{i-2}|)^2.$$

Based on the estimated integrated variance, I get "instantaneous volatility" with respect to five-minute, $\widehat{\sigma(t_j)}$, and compare it to the five-minute returns following MNAs. Lee and Mykland (2007) use a similar methodology to obtain jump test statistics. Only the announcement returns satisfying $|r_j| > \kappa\widehat{\sigma(t_j)}$ are considered as MNA shocks. I set the threshold $\kappa = 1$ for my main analysis, but the results are robust to alternative thresholds. Dropping returns with small magnitudes has two other benefits. First, announcements have various economic relevance and market impacts. The threshold mechanically restricts the sample of MNA shocks to announcements with significant market impacts. Second, including announcement returns with small magnitudes blur the distinction between positive MNA shocks and bad MNA shocks.

Previous studies show that trading volumes and volatility on stocks and equity index futures tend to be high after stock market opens and before stock market closes, which may compound my estimation of volatility. I take care of volatility periodicity following the details shown in Appendix 1.

2.3 Stock returns and firm characteristics

I obtain daily and monthly returns on US NYSE/Amex/Nasdaq stocks from CRSP. To ensure that small and illiquid stocks do not drive my results, I drop stocks with prices lower than \$5 dollar and market valuations lower than the bottom 20 percentile of the NYSE monthly market capitalization distribution. This procedure is also used by Nagel (2005), Hong and Sraer (2016), and Weber (2018). The breakpoints as well as risk-free rate, market return are all obtained from Kenneth French's online data library.

I use residual institutional ownership as a proxy for short-sales constraints. I obtain institutional ownership data from the Thomson Reuters 13F database (TR-13F). If a common stock is on CRSP but not in the TR-13, I set the institutional ownership as zero. Following Nagel (2005) and Weber (2018), I perform a logit transformation

$$logit(INST) = log(\frac{INST}{1-INST}),$$

where institutional ownership INST is winsorized at 0.0001 and 0.9999. To control for size effect, I obtain residual institutional ownership using the following quarterly Fama-Macbeth regression,

$$logit(INST_{i,t}) = \alpha + \beta_1 log(ME_{i,t}) + \beta_2 log(ME_{i,t})^2 + RI_{i,t}$$

where $log(ME)$ is the natural logarithm of size.

Analysts' forecast dispersion of earnings is an important measure of investor disagreement. Data on analyst forecasts of fiscal-year-end earnings is from Institutional Broker's Estimate System (IBES). The summary file unadjusted for stock splits is used to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). The dispersion is calculated as the standard deviation of forecast scaled by the average forecast.

To save space, the detailed definitions of other firm characteristics and risk measures are listed in Appendix A2, constructed following the convention of the literature.

3 Underreaction to macro news and its channel

In this section, I present evidence that stocks with low sensitivity to bad announcement returns underreact to bad macro news. Next, I show that the channel of underreaction is investor disagreement and short-selling constraints. Then I discuss the challenges to interpret the results with a risk-based explanation.

3.1 Sensitivity to announcement returns

Panel A of Table 2 reports the mean and standard deviation of announcement returns following good or bad macro news, as well as the number of days on which good or bad macro news are released. Good and bad MNA returns have similar magnitude and frequency. On average, there are around 33 good and bad announcements during a one-year period, and a typical announcement moves the market by about 0.25%.

To measure underreaction to bad news, I estimate sensitivity of individual stocks to bad and good announcement returns over a rolling window of 24 months using the following time-series regression

$$r_{i,t} - r_{f,t} = \alpha_i + \alpha_{i,good} I_t^{good} + \alpha_{i,bad} I_t^{bad} + \beta_{i,good} MNA_t^{good} + \beta_{i,bad} MNA_t^{bad} + \beta_{i,MKT} MKT_t + \varepsilon_{i,t}. \quad (1)$$

MNA_t^{bad} (MNA_t^{good}) is the bad (good) MNA returns on day t. If there are multiple announcements and multiple bad MNA returns on day t, I use the sum as MNA_t^{bad}. However, multiple MNA returns on the same day is rare in my sample. The rolling window of two years on average contains about 65 bad MNA returns and 65 good MNA returns.

I control for the market factor in the estimation of announcement sensitivity. As a result, instead of measuring absolute exposures to announcement returns, MNA sensitivity capture the sensitivity to macro announcements over and above what is captured by the market beta. Note that I allow the intercept to be different on trading days without announcements, with good announcements or with bad announcements. Therefore the estimation of MNA sensitivity is not compounded by the change in α_i on announcement days. Panel B of Table 2 presents descriptive statistics of good and bad MNA sensitivity. While they are both close to zero on average, there exists considerable cross-sectional variation. In particular, their standard deviation is four times larger than that of the market beta. Moreover, as I will show in Table 3, the decile portfolios sorted on bad MNA sensitivity also exhibit increasing bad sensitivity from the bottom portfolio to the top. The pattern addresses the concern that the estimated MNA sensitivity is driven by noise.

3.2 Under-performance of low sensitivity stocks

3.2.1 Portfolio analysis

If stocks with low sensitivity to bad MNA underreact to bad news, they should have low returns in the future as the mispricing is corrected, especially on days without announcements. To investigate the relation between MNA sensitivity and stock returns, I first use uni-variate portfolio sorts. Each month, stocks are sorted into decile portfolios according to their estimated bad or good MNA sensitivity. I obtain value-weighted and equal-weighted decile portfolio returns during the one-month period after the portfolio formation. Moreover, monthly returns are decomposed into two parts: returns over days with MNAs and returns over days without MNAs. I weigh each stock by its market value at the end of each estimation period. Portfolio returns are out-of-sample in the sense that there is no overlap between the time window for estimation and for post-formation returns. Rolling estimation window forward one month at a time, I repeat the procedure and obtain time series of monthly returns for all decile portfolios. I report average full monthly returns, average monthly returns over MNA days and over non-MNA days, alphas and *t*-stats concerning the Carhart four-factor model. Appendix A.2 shows similar results for equal-weighted portfolios.

Panel A of Table 3 reports value-weighted returns for the portfolios sorted by bad MNA sensitivity. Portfolio 1 consists of stocks with the lowest bad MNA sensitivity during the past 24 months, and portfolio 10 consists of stocks with the highest sensitivity. The columns labeled "Full month" in Panel A show that there is a positive and almost monotonic relation between bad MNA sensitivity and value-weighted monthly returns. Average returns on MNA days are positive, but with a limited variation from 0.68% to 1.27%. The difference in average excess return between portfolios 1 and 10 over MNA days is 0.1, with an insignificant alpha of 0.1. On non-MNA days, in contrast, average returns exhibit a strong and monotonic increase from portfolio 1 to 4. From portfolio 4 to 10 average returns are all close to zero. The value-weighted monthly return difference between decile 10 and decile 1 is 0.89% per month, with an alpha concerning Carhart four-factor model of 0.63% per month with a *t*-stat of 2.74. Although market returns are close to zero on non-MNA day (see Savor and Wilson (2013)), the last three columns show that there exists substantial variation in returns on non-MNA days.

Panel B reports the pre- and post-formation loadings of portfolios on MNA returns and Carhart four factors. The first column presents that sorting on bad MNA sensitivity leads to a wide spread in pre-formation bad MNA sensitivity across deciles. The post-formation bad sensitivity is estimated for each portfolio using unconditional full-sample daily returns. It shows a virtually monotonic increasing pattern across deciles. In other words, the sorted portfolios vary unconditionally in their exposures to bad news. Moreover, sorting on bad sensitivity generates little spread in post-formation good MNA sensitivity. It suggests that stocks exposed to bad macro news are not necessarily exposed to good news.

Panel C documents a negative relationship between good MNA sensitivity and expected returns. The long-short strategy produces an average value-weighted monthly return of -0.52%, with a Carhart four-factor alpha of -0.36% per month. -0.24% is realized on non-MNA days, but the alpha is small in magnitude and insignificant. Therefore, in the following analysis, I put emphasis on the relationship between returns and bad MNA sensitivity, though good MNA sensitivity is also included in most results.

In summary, the portfolio-level analysis shows that stocks with low bad MNA sensitivity earn economically and statistically low returns in the following month, especially on days without announcements. The results are consistent with using announcement return sensitivity as a measure of underreaction. However, these results do not take into account other known cross-sectional determinants of expected returns, which I investigate in the following section.

3.2.2 Fama-Macbeth regressions of individual stock returns

In this section, I estimate firm-level Fama-Macbeth (1973) cross-sectional regressions of monthly excess stock returns over MNA days and non-MNA days. The independent variable of interest is the bad MNA sensitivity. This firm-level analysis allows me to control for other firm and risk characteristics, including market beta, firm size, book-to-market, momentum, illiquidity, and idiosyncratic volatility. Specifically, I regress excess stock returns over MNA days or non-MNA days in month $t+1$ on MNA sensitivity and control variables measured at the end of month t. To facilitate the interpretation of economic significance, I standardize all independent variables to have a zero mean and unit variance.

Table 4 reports the results. Column (1) and (2) of Panel A show that bad and good MNA sensitivities are significantly related to full monthly returns. After including control variables, however, the magnitude of both coefficients become smaller, and the one for good MNA becomes insignificant. Column (3) and (4) show that on MNA days, there is a weak and insignificant connection between MNA sensitivity and returns. In contrast, Column (5) shows that bad sensitivity positively predicts non-MNA day returns. The coefficient is 0.13, therefore a one-standard-deviation increase in bad sensitivity predicts an increase in next month's stock return on non-MNA days of 0.13%. The inclusion of control variables makes the coefficient smaller but still highly significant, as reported in Column (6). Note that the intercept is consistently around 1% and highly significant in Column (1)-(4), but is close to zero and insignificant in Column (5) and (6). The results are consistent with Savor and Wilson (2013) that equity premium and stock market returns are higher on MNA days yet close to zero on non-MNA days. Also, the coefficients on market β change from positive to negative from MNA days to non-MNA days, consistent with Savor and Wilson (2014).

Underreaction effect should be dominant among stocks with negative sensitivity to bad MNA returns. The stocks in the long leg could underreact, but it should contain the least degree of underreaction. Panel B of Table 6 confirms the hypothesis, showing that the positive relation between bad MNA sensitivity and non-MNA day returns concentrates on stocks with lower-than-median bad MNA sensitivity. I construct a dummy variable Low_{bad} ($High_{bad}$) equal to 1 if a stock's bad MNA sensitivity is lower (higher) than the cross-sectional median at the end of a month and 0 otherwise. I interact Low_{bad} and $High_{bad}$ with bad MNA sensitivity and repeat the regressions in Panel A with control variables included. Column (3) in Panel B of Table 6 shows that the insignificant relation between bad MNA sensitivity and MNA-day returns holds for stocks with both higher- or lower-than-median sensitivity to bad news. However, Column (5) shows that stocks with lower bad MNA sensitivity have higher returns on non-MNA days, and the effect is significant only among stocks with lower-than-median sensitivity.

For completeness, I also construct Low_{good} ($High_{good}$) equal to 1 if a stock's good MNA sensitivity is higher than the median at the end of a month and 0 otherwise. Column (4) and (6) show that the coefficients on good MNA sensitivity are both insignificant for stocks higher or lower than the median.

3.3 The Channel of Underreaction

If market frictions prevent stock prices from reflecting bad news, stocks with greater short-selling constraints and investor disagreement will be less sensitive to bad macro announcements. The intuition follows the argument by Miller (1977). Consider a firm whose investors face tight short-selling constraints and disagree on how a firm should respond to macro news. Following a bad macro announcement, the stock price will not fully reflect the view of pessimist investors due to cost short-selling. Therefore, the stock tends to be overpriced, or in other words, underreact to the bad news on MNA days. As a result, stocks with high cost of short-selling and high investor disagreement should tend to have low sensitivity to the bad news. Also, as mispricing is corrected in the following days, we should observe a particularly positively relation between bad MNA sensitivity and non-MNA day returns among these stocks.

I first test the hypothesis that stocks with costly short-selling and disagreement tend to have low bad MNA sensitivity. In particular, I conduct Fama-Macbeth regressions of realized bad news sensitivity on firm and risk characteristics that are known ex ante

$$\widehat{\beta}_{i,bad,t} = \alpha + \gamma_1 Firm\ Characteristics_{i,t-24} + \gamma_2 Risk\ Characteristics_{i,t-24} + \varepsilon_{i,t}. \quad (2)$$

The bad MNA sensitivity is estimated at the end of month t, while explanatory variables is from month t-24. I use Newey-West standard error with 24 lags.

I use residual institutional ownership (RIO) to proxy for short-selling constraints following Weber (2018) and Nagel (2005). As short sellers have to borrow shares from a stock lender, and higher institutional ownership indicates higher stock loan supply (see D'avolio (2002)), low institutional ownership suggests tight short-selling constraints. I use three proxies for investor disagreement: dispersion of analysts' forecast of earnings (DISP), trading volume as a proportion of shares outstanding (TURN) at the MNA days, as well as standard error of estimated market beta of a firm. Specifically, I use one-year rolling window of daily returns to estimate a firm's market beta and its standard error. A large standard error suggests a high uncertainty on the firm's exposure to the aggregate economy, and arguably high investor disagreement on the exposure.

Panel A of Table 5 reports the estimation results. To facilitate comparison across different variables, I standardize all independent variables to have zero mean and unit variance. Regression (1) to (3) show that stocks with higher residual institutional ownership, lower analysts' forecast dispersion, lower turnover, and lower estimation standard error are more sensitive to bad macro news, suggesting that short-selling constraints and investor disagreement prevent stock prices from incorporating the beliefs of pessimistic investors on announcement days. The effect is significant except for standard error, but the magnitude is larger. With regard to other firm characteristics, value stocks exhibit higher sensitivity to bad news than growth stocks, suggesting that value stocks are more affected by an economic downturn. Stocks that are less exposed to bad news may have lower default risk, downside risk, or co-skewness. However, the coefficients on these variables are actually all insignificantly. Note that the coefficient on co-kurtosis is significantly negative, suggesting a relationship between bad MNA sensitivity and co-kurtosis. Therefore, I always control for co-kurtosis in my following regression.

Panel B of Table 5 reports the result of Fama-Macbeth regression for good MNA sensitivity. Both the downside and upside beta have a positive relationship with sensitivity to good MNA. Interestingly, residual institutional ownership, analysts' forecast dispersion, and standard error have little predictive power for sensitivity to good news. It suggests that market friction plays a minor role in how prices respond to good news.

I next test the hypothesis that the positive relation between bad news sensitivity and returns on non-MNA days concentrate on stocks with high investor disagreement and short-selling constraints. As I use three measures of disagreement, there are three pairs of constraints-disagreement combination. I test the prediction separately for each combination. For example, using analyst forecast dispersion, I estimate the following Fama-Macbeth regression on monthly returns over non-MNA days,

$$R_{i,t}^{non-MNA} = \beta_{i,t-1}^{bad} \times Low_{i,t-1} \times (\gamma_1 + \gamma_2 RIO_{i,t-1} + \gamma_3 DISP_{i,t-1} + \gamma_4 RIO_{i,t-1} DISP_{i,t-1})$$

$$+\beta_{i,t-1}^{bad} \times High_{i,t-1} \times (\eta_1 + \eta_2 RIO_{i,t-1} + \eta_3 DISP_{i,t-1} + \eta_4 RIO_{i,t-1} DISP_{i,t-1}) + controls_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where the indicator variable $Low_{i,t-1}$ ($High_{i,t-1}$) is equal to 1 if a stock i's bad MNA sensitivity is lower (higher) than the cross-sectional median at month $t-1$ and 0 otherwise. I interact RIO and DISP with lower- and higher-than-median sensitivity separately. My hypothesis predicts that the positive relation between bad MNA sensitivity and returns is particularly strong among stocks with low RIO, large DISP, and lower-than-median sensitivity ($Low_{i,t-1} = 1$). Therefore, γ_4 should be significantly negative. At the same time, tight constraints accompanied with high disagreement are less likely to lead to a positive relation between bad sensitivity and returns among stocks with high-than-median sensitivity ($High_{i,t-1} = 1$) if these stocks are less likely to be affected by underreaction in the first place. As a result, η_4 should be insignificant.

Column 1 to 3 of Table 6 presents the results where the measure of disagreement is the standard error of estimated beta, forecast dispersion, and turnover on MNA days, respectively. Across three models, the interaction between bad MNA sensitivity and Low has a significantly positive coefficient, and when further interacted with disagreement and RIO, the coefficient is significantly negative. The robust results strongly support the hypothesis that the relation between bad sensitivity and non-MNA returns is especially strong among stocks with low institutional ownership, hence tight short-selling constraints, and high investor disagreement. The economic significance is also substantial. Among stocks with average RIO and SE, a one unit decrease in bad beta leads to a lower return of 0.13% per month on non-MNA days. However, as short-selling constraints RIO decreases by one unit and investor disagreement DISP increases by one unit, the same decrease in bad beta leads to lower returns of 0.20%, with the magnitude amplified by 50%. Meanwhile, the coefficients on interaction terms for stocks with higher-than-median bad betas are insignificant and have the opposite sign, suggesting that those stocks do not experience market-friction driven underreaction.

In summary, I show that the positive relation between non-MNA day returns and bad MNA sensitivity is particularly strong among stocks with high constraints of short-selling and high investor disagreement. The results are robust to various measures of investor disagreement. Moreover, the effect is stronger during time periods when funding constraints are tighter and arbitrage capital is scarce. The overall results show that the underreaction is caused by short-selling constraints keep price from reflecting the views of pessimistic investors on days when bad macro news hits the market.

3.4 Challenges to a risk-based explanation

An alternative explanation for the positive relation between sensitivity to bad MNA and non-MNA day returns is that bad MNA sensitivity is a proxy for MNA risk, which bear a positive risk premium. However, the positive premium should be contemporaneous with the risk, and therefore exist primarily on days with MNAs, instead of on non-MNA days when investors know in advance no announcements are scheduled. Moreover, a positive price of MNA risk implies that investors should be always rewarded by higher returns for bearing more risk. But the concentration of the relation on stocks with lower-than-median bad sensitivity and on stocks with high short-selling constraints and investor disagreement suggests the opposite.

4 Mispricing: A tale of two days

Savor and Wilson (2014) show that there is a positive relation between market beta and returns on MNA days, while on non-MNA days the relation is slightly negative. In this section, I show that the results based on my sample of announcements also exhibit similar pattern, but with a much stronger negative relation on non-MNA days. Next, I provide evidence that it is driven by stocks with high market beta but low bad MNA sensitivity. The results suggest that high-beta stocks experience high returns on MNA days and low returns on non-MNA days because they underreact to bad MNA news.

4.1 The robustness of Savor and Wilson (2014)

The MNAs investigated by Savor and Wilson (2014) include only inflation, employment, and Federal Open Market Committee interest rate decision. I cover a more comprehensive set of 14 macroeconomic news announcements and confirm the positive (negative) relation between market beta and returns on MNA (non-MNA) days.

Specifically, I estimate each stock's market beta using daily returns in a rolling window of 12 months. Stocks are sorted into decile portfolios based on market beta. I calculate value-weighted and equal-weighted returns for each portfolio on days with and without MNAs. Moreover, I estimate each portfolio's market beta using daily returns also within a rolling window of 12 months, although using the whole sample leads to similar results. Panel A of Figure 2 plots average monthly excess returns on days with and without macro news announcements against market betas for the ten market beta-sorted portfolios. On days with announcements there exists a positive relationship between returns and market beta for both value-weighted and equal-weighted returns. The non-MNA days, however, show a negative relation between returns and market betas. Furthermore, compared to Figure 1 from Savor and Wilson (2014), the negative relation in Figure 2 is much stronger. A potential explanation is that Savor and Wilson (2014) report results of daily returns and they identify most trading days as non-MNA days. As a result, their monthly returns on non-MNA days are scaled by a larger number of days than monthly returns on MNA days.

Savor and Wilson (2014) also shows that there is little difference in beta conditional on announcement days or on non-announcement days. Panel B of Figure 2 presents similar results. For each of the portfolios sorted by market beta, I estimate the post-formation announcement (non-announcement) beta using only the returns on announcement (non-announcement) days. It shows that both the positive and negative relation hold equally for market betas estimated with either set of trading days.

4.2 Mispricing and the beta-return relationship

I have shown that stocks with high investor disagreement and tight short-selling constraints are more likely to underreact to bad macro news, and experience low returns in the future. These findings provide a potential explanation for the positive (negative) beta-return relation on MNA (non-MNA) days. As stocks with high market beta tend to have a high exposure to the economy, they should react more strongly to bad macro news compared with low-beta stocks. However, investors of high-beta stocks may also have more diverse beliefs. As a result of such market frictions, underreaction to bad MNA will be more pervasive for high-beta stocks. The underreaction channel leads to a testable hypothesis that among stocks with low bad MNA sensitivity, the beta-return relation on MNA days is particularly positive, and the relation on non-MNA days is particularly negative.

Using Fama-Macbeth regressions of market beta, Table 7 shows that the high-beta stocks indeed tend to have high investor disagreement. In particular, analysts forecast dispersion, turnover, and standard error are all positively and significantly related to market beta. Diether et al. (2002) document similar result that market beta is positively related to analyst forecast dispersion. Note that Liu et al. (2018) show that market beta is highly related to idiosyncratic volatility. However, the relation is greatly reduced when controlling for standard error of market beta as in column (2). The coefficients on residual institutional ownership are not consistent across regressions. The conclusion is that there is insignificant relation between market beta and residual institutional ownership. Nevertheless, given the same level of short-selling constraints, a higher level of investor disagreement still indicates that high-beta stocks experience greater degree of underreaction.

Next, Figure 3 confirms the underreaction hypothesis of the positive and negative beta-return relation using double-sorted portfolios. At the end of each month, I sort stocks into quintiles based on bad MNA sensitivity. Subsequently, I further sort stocks into quintiles based on market betas. Panel A of Figure 3 reports the value-weighted average monthly returns on bad MNA days for each portfolio. Clearly, among stocks with high market beta, those that are less sensitive to bad news have higher returns. Panel B shows that on days with good news, there is little difference in beta-return relation between stocks with high or low bad news sensitivity. More importantly, Panel C presents the monthly returns on non-MNA days. For stocks with bad MNA sensitivity in the bottom quintile, there is a pronounced downward-sloping security market line: low-beta stocks earn a monthly excess return close to zero on days without MNAs, while high-beta stocks earn an excess return of –1.45% per month, with returns decreasing monotonically in market beta. The difference in average excess returns between the two extreme market beta portfolios is -1.47% per month and highly statistically significant (t-stat equal to -2.91). However, moving to the top quintile of bad MNA sensitivity, the return difference between high and low market beta portfolios shrinks by around 50% and becomes less statistically significant.

4.3 Fama-Macbeth regression

To provide further evidence for the underreaction hypothesis, this section shows that the result is robust to controlling for other risk and firm characteristics. Table 8 reports the following Fama-Macbeth estimation on firm-level of returns on MNA days with positive announcement returns, negative announcement returns, and on non-MNA days.

$$R_{i,t+1} = \gamma_0 \times \beta_{i,t}^{CAPM} + \sum_{j=1}^{4} \gamma_j Q_{i,t}^{j} \times \beta_{i,t}^{CAPM} + controls_{i,t} + \varepsilon_{i,t+1}. \quad (4)$$

To facilitate the interpretation of economic significance, I standardize all firm characteristics as well as market beta to have zero mean and unit variance. Specifically, I separate the coefficient on market beta for stocks from different quintiles of bad MNA sensitivity. $Q_{i,t}^{j}$ is equal to 1 if a stock i is in the j'th bad beta quintile at month t and zero otherwise. The coefficient on the interaction between market beta and Q^j is the slope of security market line for the stocks from the j'th bad beta quintile. j is from 1 to 4, as I use the stocks in the top quintile as the benchmark.

The dependent variable in Column (1) and Column (2) are monthly returns on MNA days with positive announcement returns and negative announcement returns, respectively. Therefore, Column (1) and (2) cover all the MNA days, and adding (1) and (2) together leads to total monthly returns on MNA days. The first column shows that on days with positive announcement returns, there exists a positive relation between beta and return, which varies little across quintiles of sensitivity to bad news. The second column presents that on days with negative announcement returns, high beta leads to low return, but less so for stocks with $Q^1 = 1$ or $Q^2 = 1$, that is, low sensitivity to bad news. This is consistent with the idea that these stocks underreact to bad macro news. In Column (3), returns are on days without MNA. It shows that the negative relation between beta and return is -0.17 for stocks with high bad sensitivity. These are the stocks that are least likely to underreact. But for stocks with $Q^1 = 1$ which are those most likely to underreact, the negative beta-return relation is as low as -0.33, double the magnitude for stocks with high sensitivity. Moreover, the difference from the benchmark stocks are highly significant, indicating that the beta-return relation on non-MNA days is the most negative for high-beta stocks with low sensitivity to the bad news.

Overall, the results support the hypothesis that the downward-sloping security market line on days without MNA is driven by high-market-beta stocks that underreact to bad macro news and consequently experience low returns in the following non-MNA days.

4.4 Conditional market beta

Stocks that underreact to negative macro news will by definition have low conditional market beta on bad days. Therefore, it is probable that the security market line is most downward-sloping among stocks that experience sharp decrease in market beta on bad days. Therefore, I estimate for each stock the change in market beta on days when there are bad MNA shocks using the following model:

$$r_{i,t} - r_{f,t} = \alpha_i + \alpha_{i,good} I_t^{good} + \alpha_{i,bad} I_t^{bad} + \beta_{i,MKT} MKT_t + \Delta\beta_{i,good,MKT} MKT_t \times I_t^{good} + \Delta\beta_{i,bad,MKT} MKT_t \times I_t^{bad} + \varepsilon_{i,t} \quad (5)$$

where I_t^{bad} (I_t^{good}) is an indicator variable equal to 1 if on day t there exists bad (good) macro news. $\Delta\beta_{i,bad,MKT}$ ($\Delta\beta_{i,good,MKT}$) captures the change in market beta on bad (good) days. Similar to previous section, I assume $Q_{i,t}^j$ to be equal to 1 if a stock i is in the j'th quintile of $\Delta\beta_{i,bad,MKT}$ at month t and zero otherwise. With the new quintile dummy I re-estimate model (4) and the results are reported in Table 9. The coefficient on market beta is significantly negative but similar across different quintiles. The lack of disparity suggest that $\Delta\beta_{i,bad,MKT}$ is a noisy measure on weather a stock is underreacting to negative macro news.

5 Robustness Tests

Lucca and Moench (2015) report unconditional excess returns in equity index futures during 24 hours prior to the FOMC announcements. This makes the identification of MNA news not inappropriate if investors receive monetary policy information before FOMC announcements. Therefore, I present the results when FOMC is not included in the sample. Table 10 and 11 show that the main results of the paper is hardly changed when FOMC is excluded from the sample.

Co-skewness, co-kurtosis, exposure to daily changes in VIX, among other variables are included in the main regressions. However, they are not reported in tables to save space. The results of the paper are robust to these variables.

6 Conclusion

This paper examines the relationship between individual stocks' sensitivities to macroeconomic news announcements (MNAs) and the cross-section of equity returns on days with and without MNAs. Stocks with low sensitivities to bad MNA shocks tend to underperform relative to other stocks in the future, especially during days without announcements. The effect is concentrated in stocks with high investor disagreement and tight short-selling constraints. The results are consistent with the hypothesis that stocks with high shorting costs underreact to bad macroeconomic news on announcement days as pessimists' beliefs are not reflected in prices. As a result, these stocks tend to underperform in the following non-announcement day as the overpricing is corrected.

These findings provide valuable insights into the documented relationship between market beta and stock returns on MNA and non-MNA days. Savor and Wilson (2014) argue it is challenging for risk-based models to explain why market betas do not change on the two type of days, while return patterns look very different. In this paper, I provide an explanation based on mispricing. I show evidence high-beta stocks experience high returns on MNA days and low returns on non-MNA days because they underreact to bad MNA news. The results are robust to various firm characteristics and alternative estimations of bad MNA sensitivity. Overall, this study provides strong empirical evidence that underreaction to macroeconomic news announcements results in a downward-sloping security market line on days without announcements, as well as an upward-sloping security market line on days with announcements.

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Table 1: **Overview of U.S. macroeconomic announcements**

This table lists the macroeconomic announcements covered in this paper. The release time is stated in Eastern Time (ET). The dates of these announcements are obtained from official websites of Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Conference Board (CB),Federal Reserve Board (FRB), Thomson Reuters/University of Michigan (TR/UM), Institute of Supply Management (ISM) and Archival Federal Reserve Economic Data (ALFRED). For those of which the release dates are not available from official websites, I use Factiva to identify historical release dates.

Category	Announcement	Frequency	Time	Source
Employment	Initial Jobless Claims	Monthly	8:30	ETA
	Employment Situations	Monthly	8:30	BLS
Industrial Activity	Industrial Production	Monthly	9:15	FRB
	Construction Spending	Monthly	10:00	BC
	Durable Goods Orders	Monthly	8:30	BC
Consumption	Advance Retail Sales	Monthly	8:30	BC
Housing Sector	Building Permits & Housing Starts	Monthly	8:30	BC
Inflation	CPI	Monthly	8:30	BLS
Forward-looking Index	UM Consumer Sentiment Pre	Monthly	9:55	TR/UM
	UM Consumer Sentiment Final	Monthly	9:55	TR/UM
	Consumer Confidence Index	Monthly	10:00	CB
	ISM Manufacturing Index	Monthly	10:00	ISM
	ISM Non-manufacturing Index	Monthly	10:00	ISM
Monetary Policy	FOMC Announcement	8 times a year		FED

Table 2: **Summary statistics of MNA shocks and MNA sensitivity**

This table reports summary statistics of macroeconomic news announcement shocks and MNA sensitivity. Panel A reports the sample mean and standard deviation of bad and good MNA shocks in percentage. I also report the total number of MNA shocks and annual average number of shocks. Panel B reports times-series means of cross-sectional statistics of firm-level MNA sensitivity. At the end of each month, MNA sensitivity is estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months.

Panel A: Summary Statistics of MNA shocks

	Mean	Sd	Total Num	Num per year
Bad MNA	-0.26%	0.24%	656	33
Good MNA	0.25%	0.21%	684	34

Panel B: Descriptive Statistics of MNA sensitivity

Betas	Mean	SD	Skewness	Kurtosis	P25	P75
Bad MNA sensitivity	0.04	1.80	0.45	19.07	-0.84	0.95
Good MNA sensitivity	-0.11	1.79	-0.18	10.48	-1.02	0.82
CAPM β	1.11	0.46	0.75	3.95	0.78	1.36

Table 3: MNA sensitivity and expected stock returns

This table reports average value-weighted full monthly returns, monthly returns on MNA days and on non-MNA days, as well as alphas of ten portfolios sorted by bad and good MNA sensitivity. I also report for each portfolio the pre-formation average MNA sensitivity, post-formation MNA sensitivity and factor loadings on Carhart four factors. At the end of each month, I estimate MNA sensitivity using daily excess returns over the preceding 24 months. Stocks are then sorted into deciles (1-10) based on bad or good MNA sensitivity. I obtain value-weighted portfolio returns during the one-month period after the portfolio formation. Jensen alpha and the corresponding *t*-stat of each decile portfolio are estimated with respect to Carhart four-factor model.

Panel A: Performance of value-weighted portfolios sorted by bad MNA sensitivity

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.16	-0.37	-1.30	1.17	0.09	0.44	-1.01	-0.47	-2.49
2	0.19	-0.24	-1.35	0.89	0.03	0.21	-0.70	-0.27	-2.41
3	0.35	-0.08	-0.55	0.78	0.01	0.07	-0.43	-0.08	-0.90
4	0.47	0.03	0.24	0.75	0.03	0.35	-0.28	-0.00	-0.03
5	0.51	0.04	0.41	0.68	-0.06	-0.73	-0.17	0.10	1.45
6	0.58	0.08	0.72	0.68	-0.08	-0.89	-0.10	0.16	2.23
7	0.77	0.26	2.20	0.86	0.10	1.11	-0.10	0.16	2.08
8	0.84	0.28	2.20	0.87	0.05	0.48	-0.03	0.24	2.83
9	0.81	0.17	1.20	0.94	0.04	0.37	-0.13	0.13	1.46
10	1.15	0.36	2.01	1.27	0.20	1.42	-0.12	0.17	1.43
.									
High-Low	0.99	0.73	2.05	0.10	0.10	0.38	0.89	0.63	2.74
9-2	0.61	0.41	1.51	0.04	0.01	0.05	0.57	0.40	2.32

Panel B: Characteristics of value-weighted portfolios sorted by bad MNA sensitivity

	pre-formation			post-formation					
Portfolio	Bad	Good	β_{MKT}	Bad	Good	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-3.05	-0.12	1.37	-0.22	0.06	1.27	0.32	-0.40	-0.34
2	-1.38	-0.15	1.14	-0.05	-0.05	1.09	0.05	-0.32	-0.17
3	-0.82	-0.12	1.05	-0.03	-0.04	0.97	-0.03	-0.16	-0.09
4	-0.43	-0.11	1.01	-0.03	-0.10	0.90	-0.08	-0.02	0.01
5	-0.11	-0.08	1.00	0.00	-0.18	0.91	-0.10	0.06	0.00
6	0.19	-0.08	1.00	0.06	0.00	0.94	-0.13	0.09	0.05
7	0.51	-0.08	1.02	0.09	0.08	0.94	-0.11	0.12	0.06
8	0.88	-0.07	1.06	0.02	-0.00	0.98	-0.07	0.21	0.04
9	1.40	-0.09	1.12	0.07	0.06	1.06	0.02	0.17	0.09
10	2.92	-0.08	1.28	-0.03	0.15	1.22	0.28	0.14	0.10

Table 3: Continued

Panel C: Performance of value-weighted portfolios, sorted by good MNA sensitivity

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.82	0.05	0.28	1.14	0.05	0.32	-0.32	0.01	0.05
2	0.64	-0.01	-0.04	0.88	-0.03	-0.31	-0.24	0.03	0.28
3	0.81	0.26	2.12	0.99	0.14	1.40	-0.18	0.13	1.65
4	0.50	0.04	0.32	0.88	0.09	0.92	-0.38	-0.05	-0.63
5	0.59	0.10	0.81	0.86	0.09	0.99	-0.27	0.01	0.13
6	0.57	0.13	1.09	0.82	0.09	1.04	-0.25	0.04	0.47
7	0.70	0.26	2.35	0.77	0.03	0.38	-0.07	0.23	3.24
8	0.43	-0.07	-0.59	0.81	0.01	0.12	-0.38	-0.08	-1.07
9	0.30	-0.17	-1.34	0.71	-0.07	-0.71	-0.41	-0.10	-1.23
10	0.30	-0.30	-1.68	0.86	-0.13	-0.94	-0.56	-0.18	-1.48
High-Low	-0.52	-0.36	-1.25	-0.28	-0.17	-0.80	-0.24	-0.18	-1.00
9-2	-0.33	-0.17	-0.76	-0.16	-0.04	-0.22	-0.17	-0.13	-0.92

Panel D: Characteristics of value-weighted portfolios, sorted by good MNA sensitivity

	pre-formation			post-formation					
Portfolio	Good	Bad	β_{MKT}	Good	Bad	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-2.76	-0.10	1.25	-0.13	-0.16	1.19	0.26	0.34	-0.04
2	-1.35	-0.00	1.11	-0.16	-0.12	1.02	0.09	0.31	0.02
3	-0.87	0.00	1.06	-0.14	0.00	1.02	-0.05	0.13	-0.01
4	-0.52	0.01	1.02	-0.13	-0.07	0.97	-0.03	-0.05	-0.07
5	-0.23	0.03	1.01	0.02	-0.00	0.97	-0.09	-0.03	0.04
6	0.05	0.04	1.01	0.04	-0.04	0.94	-0.13	-0.06	0.02
7	0.35	0.07	1.01	-0.02	-0.05	0.94	-0.15	-0.00	0.00
8	0.69	0.06	1.04	0.04	-0.03	0.98	-0.05	-0.03	-0.00
9	1.16	0.07	1.10	0.04	0.16	0.99	-0.05	-0.11	0.02
10	2.61	-0.04	1.30	0.04	0.11	1.18	0.19	-0.18	-0.06

Table 4: Stock-level Fama-MacBeth regressions

This table reports results from stock-level Fama-MacBeth regressions of full monthly returns, monthly returns on MNA days and on non-MNA days. MNA sensitivity is estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. Control variables include size, book-to-Market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. to have a zero mean and unit variance. Low^{bad} (Low^{good}) is equal to one if a stock's bad (good) MNA sensitivity is lower than the cross-sectional median at the end of a month. $High^{bad}$ ($high^{good}$) is equal to one if a stock's bad (good) MNA sensitivity is higher than the cross-sectional median at the end of a month. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4: Continued

Panel A: Fama-Macbeth regressions of monthly returns

	Full month		MNA days		non-MNA days	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad MNA sensitivity	0.14**	0.061*	0.015	-0.0089	0.13***	0.069***
	(2.09)	(1.68)	(0.28)	(-0.29)	(2.96)	(2.70)
Good MNA sensitivity	-0.16***	-0.031	-0.051	0.012	-0.11***	-0.040*
	(-3.06)	(-0.92)	(-1.25)	(0.44)	(-3.11)	(-1.67)
MKT β		-0.13		0.16		-0.27***
		(-0.80)		(1.40)		(-2.63)
Size		-0.20***		-0.083		-0.10*
		(-2.72)		(-1.51)		(-1.93)
BM		-0.013		0.016		-0.024
		(-0.25)		(0.44)		(-0.73)
MOM		0.041		-0.016		0.059
		(0.37)		(-0.21)		(0.89)
ILLIQ		0.010		0.11		-0.084
		(0.10)		(1.16)		(-1.25)
IVOL		-0.024		0.12		-0.13
		(-0.18)		(1.44)		(-1.40)
REV		-0.24***		-0.28***		0.032
		(-2.69)		(-4.14)		(0.63)
Max		0.11		0.031		0.070
		(1.23)		(0.50)		(1.26)
Min		0.043		0.13**		-0.099*
		(0.52)		(2.19)		(-1.69)
Coskew		0.12		0.029		0.084
		(1.08)		(0.45)		(1.60)
Cokurt		0.11		0.064		0.039
		(1.05)		(0.99)		(0.76)
Constant	1.02***	0.99***	1.09***	1.04***	-0.017	-0.00041
	(2.91)	(2.77)	(3.81)	(3.61)	(-0.06)	(-0.00)
r2	0.011	0.10	0.011	0.091	0.011	0.10
N	383038	362552	383038	362552	383038	362552

Table 4: Continued

Panel B: Piecewise Fama-Macbeth regressions of monthly returns

	Full month		MNA days		non-MNA days	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad MNA sensitivity × Low^{bad}	0.085		-0.010		0.088**	
	(1.53)		(-0.25)		(2.26)	
Bad MNA sensitivity × $High^{bad}$	0.036		-0.0059		0.048	
	(0.58)		(-0.12)		(1.19)	
Good MNA sensitivity × Low^{good}		0.019		0.074		-0.047
		(0.33)		(1.62)		(-1.14)
Good MNA sensitivity × $High^{good}$		-0.080		-0.054		-0.028
		(-1.49)		(-1.27)		(-0.71)
Bad MNA sensitivity		0.060*		-0.0086		0.068***
		(1.67)		(-0.28)		(2.68)
Good MNA sensitivity	-0.031		0.011		-0.039	
	(-0.91)		(0.41)		(-1.62)	
MKT β	-0.12	-0.12	0.16	0.16	-0.27***	-0.27***
	(-0.79)	(-0.79)	(1.40)	(1.42)	(-2.63)	(-2.65)
Size	-0.20***	-0.20***	-0.083	-0.084	-0.10**	-0.10*
	(-2.77)	(-2.76)	(-1.52)	(-1.53)	(-1.98)	(-1.96)
BM	-0.013	-0.015	0.014	0.014	-0.022	-0.024
	(-0.26)	(-0.30)	(0.39)	(0.39)	(-0.69)	(-0.76)
MOM	0.042	0.046	-0.016	-0.011	0.060	0.060
	(0.38)	(0.41)	(-0.21)	(-0.15)	(0.90)	(0.90)
ILLIQ	0.0079	0.0100	0.11	0.12	-0.082	-0.086
	(0.08)	(0.10)	(1.14)	(1.16)	(-1.21)	(-1.26)
IVOL	-0.031	-0.012	0.12	0.13	-0.13	-0.12
	(-0.24)	(-0.09)	(1.36)	(1.54)	(-1.42)	(-1.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.10	0.10	0.093	0.093	0.10	0.10
N	362552	362552	362552	362552	362552	362552

Table 5: MNA sensitivity and firm characteristics

This table reports the results of monthly Fama-Macbeth regressions of bad and good MNA sensitivity on firm characteristics. At the end of each month, MNA sensitivity is estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. I match MNA sensitivity with firm characteristics and risk measures known 24 months ago. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Panel A reports the regression results for bad MNA sensitivity, and Panel B reports the results for good MNA sensitivity. The *t*-statistics are calculated using Newey-West *t*-statistic with 24 lags and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5: Continued

Panel A: Bad MNA sensitivity

	(1)	(2)	(3)
RIO	0.0229***	0.0219***	0.0181**
	(2.63)	(2.90)	(2.54)
DISP	-0.0363**		
	(-2.44)		
TURN		-0.0565***	
		(-3.94)	
SE			-0.0875
			(-1.13)
Size	-0.0250	-0.0274	-0.0394
	(-0.61)	(-0.71)	(-1.06)
BM	0.0323	0.0282	0.0228
	(1.11)	(1.17)	(0.95)
Downside β	-0.0146	-0.00239	0.00378
	(-0.39)	(-0.07)	(0.13)
Upside β	0.00416	0.00813	0.00216
	(0.24)	(0.50)	(0.11)
Coskew	-0.00796	-0.0165	-0.0148
	(-0.43)	(-0.92)	(-0.86)
Cokurt	-0.0553**	-0.0665***	-0.0642***
	(-2.34)	(-3.08)	(-3.19)
O-score	-0.0461	-0.0350	-0.0341
	(-1.44)	(-1.23)	(-1.34)
ILLIQ	0.00336	-0.00510	0.00481
	(0.12)	(-0.45)	(0.48)
r2	0.0688	0.0643	0.0814
N	225592	253018	253060

Table 5: Continued

Panel B: Good MNA sensitivity

	(1)	(2)	(3)
RIO	-0.0138	-0.0104	-0.0104
	(-0.82)	(-0.73)	(-0.75)
DISP	0.0125		
	(0.76)		
TURN		0.0192	
		(1.10)	
SE			-0.0365
			(-0.72)
Size	0.0520	0.0593	0.0486
	(1.07)	(1.00)	(0.79)
BM	-0.0108	-0.00550	-0.00872
	(-0.42)	(-0.26)	(-0.45)
Downside β	0.0258	0.0171	0.0255
	(1.09)	(0.74)	(1.23)
Upside β	0.0390	0.0399	0.0406
	(1.07)	(1.15)	(1.16)
Coskew	-0.00145	-0.00496	-0.000305
	(-0.08)	(-0.35)	(-0.02)
Cokurt	-0.0371**	-0.0418***	-0.0370**
	(-2.09)	(-2.64)	(-2.44)
O-score	-0.0297	-0.0300	-0.0300
	(-0.62)	(-0.65)	(-0.66)
ILLIQ	-0.0148	0.0291	0.0260
	(-0.24)	(0.99)	(0.89)
r2	0.0718	0.0665	0.0762
N	225592	253018	253060

Table 6: Stock-level Fama-MacBeth regressions: Disagreement and short-selling constraints

This table reports results from stock-level Fama-MacBeth regressions of full monthly returns, monthly returns on MNA days and non-MNA days. MNA sensitivity is estimated by regressing daily stock returns on good and bad MNA shocks over the past 24 months, controlling for the market factor. Market beta is estimated at the end of each month using daily returns over the past 12 months. High (Low) is equal to one if a stock's bad MNA sensitivity is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include size, book-to-market, momentum, illiquidity, return reversal, maximum and minimum daily return over the past month, co-skewness, co-kurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6: Continued

	(1) SE	(2) DISP	(3) TURN
Bad MNA sensitivity × Low	0.13***	0.10**	0.085**
	(3.15)	(2.31)	(2.03)
Bad MNA sensitivity × Low × RIO	-0.013	-0.041	-0.0097
	(-0.34)	(-1.30)	(-0.29)
Bad MNA sensitivity × Low × DISA	-0.037	0.014	0.023
	(-0.89)	(0.36)	(0.59)
Bad MNA sensitivity × Low × RIO × DISA	-0.067**	-0.096***	-0.060*
	(-2.13)	(-2.73)	(-1.85)
Bad MNA sensitivity × High	0.052	0.049	0.032
	(1.23)	(1.01)	(0.75)
Bad MNA sensitivity × High × RIO	0.030	0.032	0.036
	(0.83)	(0.82)	(0.97)
Bad MNA sensitivity × High × DISA	0.015	-0.060	0.11**
	(0.33)	(-1.39)	(2.21)
Bad MNA sensitivity × High × RIO × DISA	0.011	0.017	0.042
	(0.26)	(0.29)	(1.05)
MKT β	-0.28***	-0.26**	-0.25**
	(-2.83)	(-2.55)	(-2.54)
Size	-0.093*	-0.092*	-0.11**
	(-1.95)	(-1.79)	(-2.16)
BM	-0.018	-0.012	-0.025
	(-0.64)	(-0.32)	(-0.87)
MOM	0.053	0.056	0.062
	(0.87)	(0.84)	(0.95)
ILLIQ	0.021	0.048	-0.0018
	(0.71)	(0.90)	(-0.07)
IVOL	-0.12*	-0.073	-0.083
	(-1.65)	(-0.83)	(-0.97)
Controls	Yes	Yes	Yes
r2	0.12	0.12	0.12
N	361835	318886	361760

Table 7: Market beta and firm characteristics

This table reports the results of monthly Fama-Macbeth regressions of market beta on firm characteristics. At the end of each month, market beta is estimated using daily returns over previous 12 months. I match market beta with firm characteristics known 12 months ago. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. The *t*-statistics are calculated using Newey-West *t*-statistic with 12 lags and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
RIO	-0.00212	0.00495**	-0.00195	-0.00358
	(-0.85)	(2.05)	(-0.77)	(-1.40)
SE		0.197***		
		(10.16)		
DISP			0.0248***	
			(6.70)	
TURN				0.0747***
				(8.30)
Size	-0.0650***	-0.0259	-0.0632***	-0.0507***
	(-3.64)	(-1.64)	(-3.64)	(-2.88)
BM	-0.0121	0.00760	-0.0167	-0.00987
	(-0.87)	(0.81)	(-1.00)	(-0.74)
ILLIQ	-0.0361**	-0.0205*	-0.0197	-0.0121
	(-2.34)	(-1.83)	(-0.88)	(-0.98)
Coskew	-0.00563	0.00215	-0.00648	-0.00353
	(-0.35)	(0.18)	(-0.37)	(-0.24)
Cokurt	0.00658	0.0158	0.00631	0.00975
	(0.53)	(1.63)	(0.46)	(0.86)
O-score	-0.0246***	-0.0292***	-0.0281***	-0.0243***
	(-3.06)	(-4.46)	(-3.23)	(-3.19)
IVOL	0.153***	0.0369***	0.148***	0.126***
	(10.34)	(9.01)	(9.95)	(10.39)
Constant	1.091***	1.119***	1.094***	1.091***
	(32.71)	(44.74)	(31.47)	(32.80)
r2	0.251	0.338	0.266	0.272
N	317183	297464	281003	317128

Table 8: Stock-level Fama-MacBeth regressions on market beta

This table reports results from Fama-MacBeth regressions of monthly returns on market beta. The dependent variable in Column 1 is monthly returns on days with positive announcement returns. The dependent variable in Column 2 is monthly returns on days with negative announcement returns. The dependent variable in Column 3 is monthly returns on non-MNA days. Q^j is equal to 1 if a particular stock's bad sensitivity is in the j'th quintile at month t and zero otherwise. Market β is estimated by a regression of daily excess returns on market factor over a 12-months window. Control variables include firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), return reversal, maximum and minimum daily return over the past month, co-skewness, and co-kurtosis. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
MKT β	0.41***	-0.21***	-0.17*
	(4.21)	(-2.61)	(-1.69)
MKT $\beta \times Q^1$	-0.0054	0.11*	-0.16***
	(-0.10)	(1.77)	(-2.62)
MKT $\beta \times Q^2$	0.019	0.11**	-0.12**
	(0.38)	(2.24)	(-2.34)
MKT $\beta \times Q^3$	-0.033	0.033	-0.095*
	(-0.75)	(0.76)	(-1.95)
MKT $\beta \times Q^4$	-0.040	0.056	-0.030
	(-1.02)	(1.34)	(-0.60)
Size	-0.042	-0.024	-0.12**
	(-1.06)	(-0.66)	(-2.36)
BM	0.0092	0.0029	-0.028
	(0.41)	(0.13)	(-0.96)
MOM	-0.015	-0.020	0.060
	(-0.32)	(-0.43)	(0.94)
ILLIQ	0.022	0.12	-0.098
	(0.95)	(1.17)	(-1.31)
IVOL	0.034	0.059	-0.14**
	(0.67)	(1.27)	(-2.21)
Controls	Yes	Yes	Yes
r2	0.10	0.089	0.10
N	361663	361663	361663

Table 9: Stock-level Fama-MacBeth regressions on market beta: Conditional market beta

This table reports results from Fama-MacBeth regressions of monthly returns during non-MNA days on market beta. $Q^j_{i,t}$ is equal to 1 if a stock i is in the j'th quintile of $\Delta\beta_{i,bad,MKT}$ at month t and zero otherwise. Market β is estimated by a regression of daily excess returns on market factor over a 12-months window. Control variables include firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), return reversal, maximum and minimum daily return over the past month, co-skewness, and co-kurtosis. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)
MKT $\beta \times Q^1$	-0.25**	-0.27**
	(-1.99)	(-2.58)
MKT $\beta \times Q^2$	-0.25**	-0.25**
	(-1.99)	(-2.38)
MKT $\beta \times Q^3$	-0.22*	-0.24**
	(-1.75)	(-2.42)
MKT $\beta \times Q^4$	-0.23*	-0.24**
	(-1.86)	(-2.39)
MKT $\beta \times Q^5$	-0.30**	-0.30***
	(-2.25)	(-2.88)
Size		-0.098*
		(-1.90)
BM		-0.021
		(-0.69)
MOM		0.048
		(0.66)
ILLIQ		-0.082
		(-1.01)
IVOL		-0.10
		(-1.13)
Controls	No	Yes
r2	0.048	0.098
N	383038	361835

Table 10: Robustness test: Stock-level Fama-Macbeth regressions on bad MNA sensitivity

This table reports results from Fama-MacBeth regressions of monthly returns over non-MNA days. FOMC is excluded from the sample of announcements. High (Low) is equal to one if a stock's bad MNA sensitivity is higher (lower) than the cross-sectional median at the end of a month and zero otherwise. RIO is defined as the residual in a cross-sectional regression of the percentage of shares held by institutional investors on market capitalization. DISP is defined as the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts on the current month scaled by the absolute value of the mean forecast. IVOL is defined as the standard deviation of the residuals from the regression of daily excess returns on Fama-French 3 factors over a one-months window. TURN is computed as the percentage of shares outstanding that is traded in the last month. Other controls include firm size (Size), Book-to-Market (BM), momentum (MOM), illiquidity (ILLIQ), reversal, maximum daily return, minimum daily return, coskewness, cokurtosis, as well as interactions of High (Low) with RIO, DISP, IVOL, and TURN. All of the betas and firm characteristics are standardized, i.e., demeaned and divided by standard deviation, cross-sectionally within each month. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 10: Continued

	(1) SE	(2) DISP	(3) TURN
Bad MNA sensitivity × Low	0.12***	0.093**	0.078*
	(3.10)	(2.16)	(1.92)
Bad MNA sensitivity × Low × RIO	-0.0079	-0.036	-0.0049
	(-0.21)	(-1.15)	(-0.15)
Bad MNA sensitivity × Low × DISA	-0.041	0.012	0.020
	(-1.00)	(0.32)	(0.50)
Bad MNA sensitivity × Low × RIO × DISA	-0.069**	-0.097***	-0.061*
	(-2.18)	(-2.71)	(-1.87)
Bad MNA sensitivity × High	0.045	0.045	0.026
	(1.12)	(0.97)	(0.63)
Bad MNA sensitivity × High × RIO	0.032	0.034	0.038
	(0.88)	(0.86)	(1.05)
Bad MNA sensitivity × High × DISA	0.019	-0.061	0.11**
	(0.41)	(-1.41)	(2.26)
Bad MNA sensitivity × High × RIO × DISA	0.0094	0.015	0.039
	(0.23)	(0.25)	(0.98)
MKT β	-0.28***	-0.26**	-0.25**
	(-2.87)	(-2.58)	(-2.55)
Size	-0.099**	-0.098*	-0.12**
	(-2.08)	(-1.94)	(-2.30)
BM	-0.014	-0.0069	-0.021
	(-0.53)	(-0.20)	(-0.74)
MOM	0.055	0.058	0.064
	(0.93)	(0.90)	(1.03)
ILLIQ	0.024	0.051	0.00056
	(0.80)	(0.96)	(0.02)
IVOL	-0.13*	-0.077	-0.088
	(-1.72)	(-0.88)	(-1.04)
Controls	Yes	Yes	Yes
r2	0.12	0.12	0.12
N	361835	318886	361760

Table 11: Robustness test: Stock-level Fama-Macbeth regressions on market beta

This table reports results from Fama-MacBeth regressions of monthly returns on market beta. FOMC is excluded from the sample of announcements. The dependent variable in Column 1 is monthly returns on days with positive announcement returns. The dependent variable in Column 2 is monthly returns on days with negative announcement returns. The dependent variable in Column 3 is monthly returns on non-MNA days. At the end of each month, market beta is estimated using daily returns over previous 12 months. $Q_{i,t}^{j}$ is equal to 1 if a stock i is in the j'th quintile at month t and zero otherwise. Control variables include firm size (Size), book-to-market ratio (BM), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), momentum (MOM), reversal return, maximum daily return, minimum daily return, co-skewness, and co-kurtosis. Firm characteristics are standardized, i.e. demeaned and divided by standard deviation, cross-sectionally within each month. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
MKT β	0.39***	-0.21**	-0.17
	(4.05)	(-2.54)	(-1.56)
MKT $\beta \times Q^1$	0.013	0.14**	-0.16**
	(0.22)	(2.30)	(-2.53)
MKT $\beta \times Q^2$	0.037	0.082	-0.097*
	(0.72)	(1.64)	(-1.68)
MKT $\beta \times Q^3$	0.0017	0.051	-0.12**
	(0.04)	(1.06)	(-2.15)
MKT $\beta \times Q^4$	-0.021	0.040	-0.076
	(-0.46)	(0.93)	(-1.43)
Size	-0.044	-0.024	-0.12**
	(-1.11)	(-0.65)	(-2.39)
BM	0.0080	0.0011	-0.027
	(0.36)	(0.05)	(-0.95)
MOM	-0.015	-0.020	0.057
	(-0.30)	(-0.43)	(0.90)
ILLIQ	0.022	0.12	-0.099
	(0.93)	(1.19)	(-1.29)
IVOL	0.032	0.059	-0.14**
	(0.64)	(1.26)	(-2.23)
Controls	Yes	Yes	Yes
r2	0.10	0.089	0.10
N	361334	361334	361334

Figure 1: Volatility of one-minute returns around macro announcements

This figure plots the standard deviation of one-minute returns on E-mini S&P 500 futures around MNA shocks for the period of 1997-2017. Returns are expressed as percentages. The horizontal axis marks the ordinal number of the one-minute intervals around announcement time point. Specifically, number t from -6 to 6 is defined as the t'th one-minute interval after (positive t) or before (negative t) announcement time.

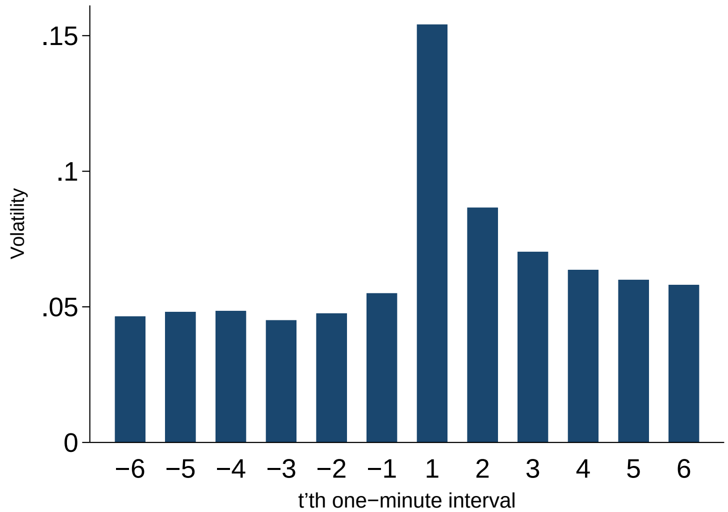
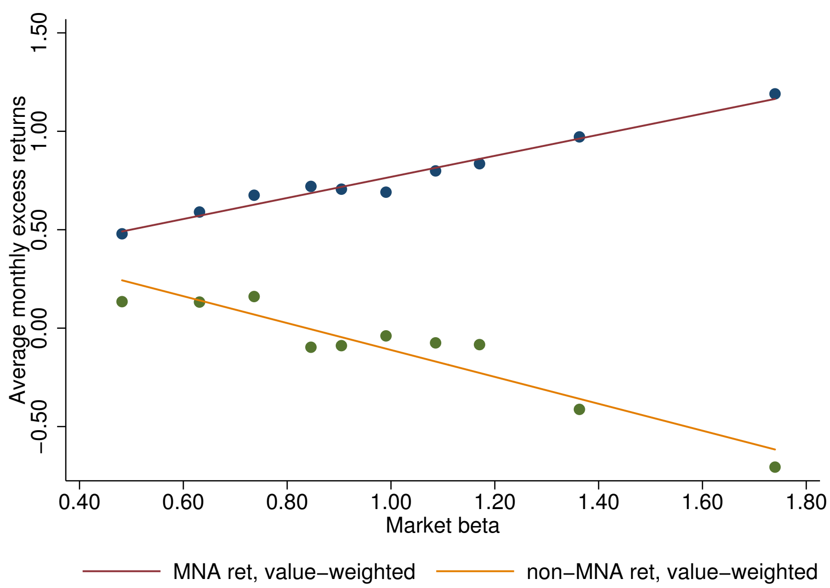


Figure 2: Average excess returns for 10 market beta-sorted portfolios

This figure plots average monthly excess returns on days with and without macro news announcements against market betas for 10 market beta-sorted portfolios. Individual stock market betas are estimated at the end of each month using daily returns in a rolling window of 12 months. Stocks are then sorted into decile portfolios based on the market beta. Portfolios are rebalanced monthly. Value-weighted and equal-weighted returns are calculated for each portfolio on days with and without MNAs. Panel A estimates portfolio market beta using all days. Panel B estimates market beta for MNA days and non-MNA days separately. Returns are expressed as percentages.

Panel A: Portfolio returns on MNA and non-MNA days



Panel B: Portfolio returns on MNA and non-MNA days

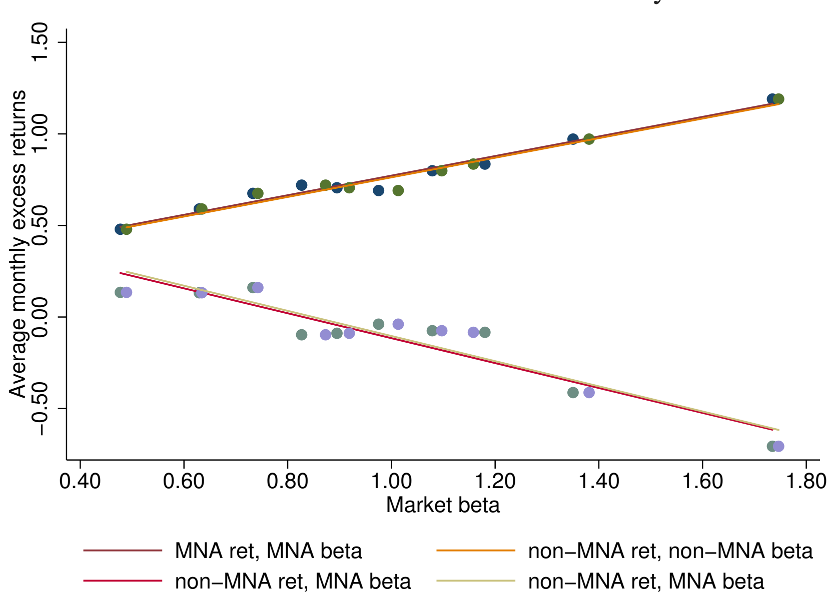
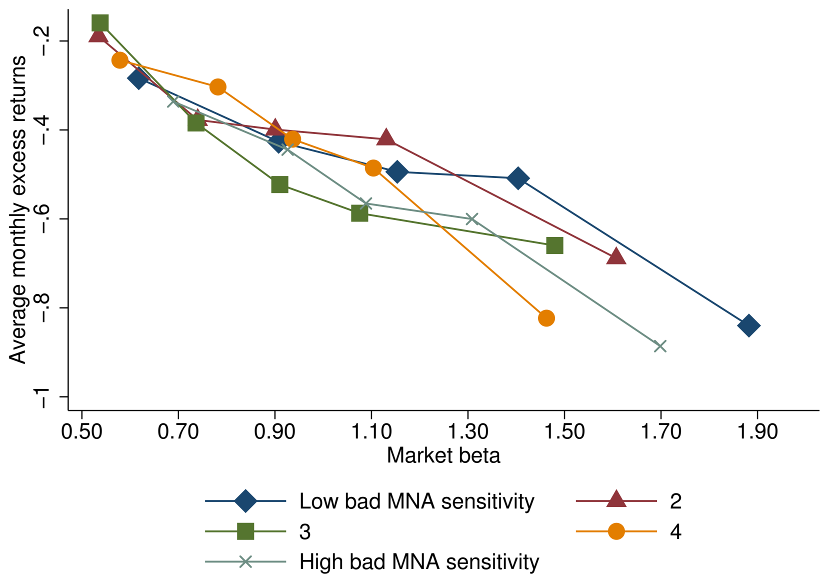


Figure 3: Average excess returns on 25 double-sorted portfolios

This figure plots average value-weighted monthly returns against market beta on days with good or bad macro news, and on days without macro news announcements for 25 double-sorted portfolios. At the end of each month stocks are first sorted into quintiles based on bad MNA sensitivity and subsequently into quintiles based on market beta. Portfolios are rebalanced monthly. Portfolio market betas are estimated over the whole sample. Returns are expressed as percentages.

Panel A: Portfolio returns on bad MNA days



Panel B: Portfolio returns on good MNA days

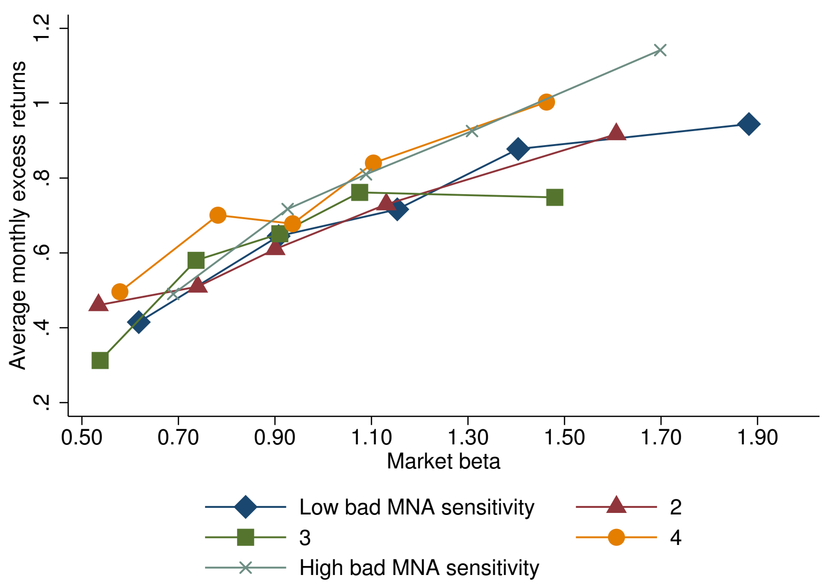
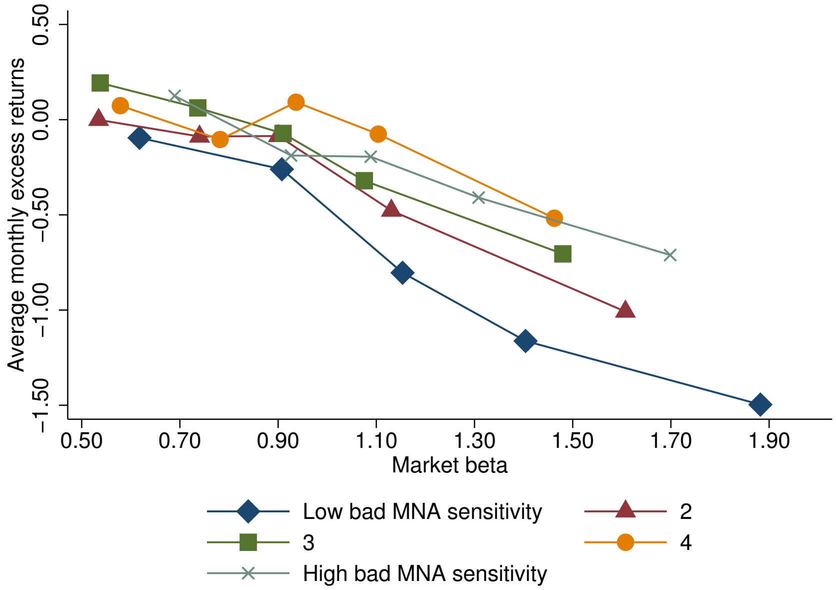


Figure 4: Continued

Panel C: 25 double-sorted portfolio returns on non-MNA days



Appendix

A.1 Periodicity

I control volatility periodicity following the non-parametric weighted standard deviation (WSD) estimator in Boudt et al. (2011) which is built on shortest half estimator. For each year I estimate the periodicity factor which varies across the day of the week and the $j'th$ interval during the day. Suppose $r_j = \{r_{(1),j}, r_{(2),j}, r_{(3),j}, ..., r_{(T),j}\}$ is the vector of returns observed on the the time j of the day and a certain day of the week (e.g. Friday), such that $r_{(1),j} \leq r_{(2),j} \leq r_{(3),j} \leq, ... \leq r_{(T),j}$. The shortest half scale is

$$ShortH_j = 0.741 \times min\{r_{(h_i),j} - r_{(1),j}, ..., r_{(T_i),j} - r_{(T-h+1),j}\},\ where\ h = [T/2] + 1.$$

Suppose there are L observations during a day, the shortest half scale estimator for periodicity at time j on that day of the week is then defined as $f_j^{ShortH} = \frac{ShortH_j}{\sqrt{\frac{1}{L}\sum_{l=1}^{L} ShortH_l^2}}$. The WSD periodicity factor related to timing j is defined as $f_j^{WSD} = \frac{WSD_j}{\sqrt{\frac{1}{L}\sum_{l=1}^{L} WSD_l^2}}$, where $WSD_j = \sqrt{1.081 \frac{\sum_{t=1}^{T} w_{t,j} \times r_{t,j}^2}{\sum_{t=1}^{T} w_{t,j}}}$ and $w_{t,j} = 1$ if $r_{t,j}/f_j^{ShortH} <= 6.635$ and 0 otherwise.

I scale five-minute returns with WSD periodicity factor and use the scaled returns to estimate instantaneous volatility. Specifically, suppose $r_{t,j}$ on day t over the $j'th$ interval of five-minute during the day as an WSD-scaled announcement return , I estimate the local "instantaneous volatility" with respect to five-minute as

$$\widehat{\sigma_{t,j}}^2 = \frac{\pi}{6 - 4\sqrt{3} + \pi} \times \frac{1}{K-2} \sum_{i=j-K+2}^{j-1} med(|r_{t,i}|, |r_{t,i-1}|, |r_{t,i-2}|)^2,$$

with $K = 5 \times 96$.

A2.Variable Definition

- **Analysts' forecast dispersion of earnings (DISP)**: Data on analyst forecasts of fiscal-year-end earnings is from Institutional Broker's Estimate System (IBES). The summary file unadjusted for stock splits is used to avoid the bias induced by ex-post split adjustment, as pointed out by Diether, Malloy, and Scherbina (2002). The dispersion is calculated as the standard deviation of forecast scaled by the average forecast.

- **Book-to-Market (BM)**: I following Novy-Marx (2013) and measure book equity as shareholder equity, plus deferred taxes, minus preferred stock, when available, for the fiscal year ending in the calendar year t-1. If shareholder equity is missing, I calculate it as the sum of the book value of common and preferred equity. If all of these are missing, we calculate shareholder equity as total assets minus total liabilities. Market value of equity is stock price times shares outstanding at the end of December of year t – 1.

- **Downside beta** β_i^-: The downside beta at the end of month t is estimated using the following model of daily returns over the past 12 months, $r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_i^- \times MKT_d + \varepsilon_{i,d}$ on the condition that $MKT_d < \mu_m$, where μ_m is the average market excess return.

- **Idiosyncratic volatility (IVOL)**: Following Ang et al. (2006b), idiosyncratic volatility at the end of month t as $ivol_{i,t} = \sqrt{var(\varepsilon_{i,t})}$, where $\varepsilon_{i,t}$ is the error term of the Fama and French (1993) three-factor regression. The regression is estimated using daily returns over month t.

- **Illiquidity (ILLIQ)**: Following Amihud (2002), I calculate illiquidity of stock i at the end of month tas the average daily ratio of the absolute stock return to the dollar trading volume of that month:

$$ILLQ_{i,t} = \frac{1}{N}\sum_d\left(\frac{|r_{i,d}|}{volume_{i,d} \times price_{i,d}}\right),$$

where N is the number of trading days in month t, $r_{i,d}$ is the daily return, $volume_{i,d}$ is the daily trading volume, and $price_{i,d}$ is the daily price on day d.

- **Maximum daily return (MAX)**: MAX of month t is defined as the maximum daily return of that month, following Bali et al. (2011).

• **Momentum (MOM)**: The cumulative return over the past 12 months, skipping the return in the last month.

• **MKT beta**: The regular market β at the end of month t is estimated using the following model of daily returns over the past 12 months,

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i \times MKT_d + \varepsilon_{i,d},$$

where $r_{i,d}$ is the return on stock i, MKT is the market factor, and $r_{f,d}$ is the risk-free rate.

• **Reversal (REV)**: REV in month t is defined as the monthly stock return over the month.

• **Residual institutional ownership (RIO)**: I obtain institutional ownership data from the Thomson Reuters 13F database (TR-13F). If a common stock is on CRSP but not in the TR-13, I set the institutional ownership as zero. Following Nagel (2005) and Weber (2018), I perform a logit transformation

$$logit(INST) = log(\tfrac{INST}{1-INST}),$$

where institutional ownership INST is winsorized at 0.0001 and 0.9999. To control for size effect, I obtain residual institutional ownership using the following quarterly Fama-Macbeth regression,

$$logit(INST_{i,t}) = \alpha + \beta_1 log(ME_{i,t}) + \beta_2 log(ME_{i,t})^2 + RI_{i,t} + \varepsilon_{i,t}$$

where $log(ME)$ is the natural logarithm of size.

• **Standard error of estimated market beta (SE)**: The standard error of the estimated market β at the end of month t is estimated using the following model of daily returns over the past 12 months,

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i \times MKT_d + \varepsilon_{i,d},$$

where $r_{i,d}$ is the return on stock i, MKT is the market factor, and $r_{f,d}$ is the risk-free rate.

• **Size**: The natural logarithm of the market value of equity (the product of closing price and the number of shares outstanding) at the end of each month.

- **Turnover (TURN)**: The turnover in month t is measured as the ratio of the number of shares traded during the month divided by the number of shares outstanding at the end of the month.
- **Upside beta** β_i^+: The upside beta at the end of month t is estimated using the following model of daily returns over the past 12 months, $r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_i^+ \times MKT_d + \varepsilon_{i,d}$ on the condition that $MKT_d > \mu_m$, where μ_m is the average market excess return.

A3. Additional Tables

Table 12: MNA Sensitivity and expected stock returns

This table reports average equal-weighted full monthly returns, monthly returns on MNA days and non-MNA days, as well as alphas of ten portfolios sorted by bad and good MNA sensitivity. I also report for each portfolio the pre-formation average MNA sensitivity, post-formation MNA sensitivity and factor loadings on Carhart four factors. At the end of each month, I estimate MNA sensitivity using daily excess returns over the preceding 24 months. Stocks are then sorted into deciles (1-10) based on bad or good MNA sensitivity. I obtain equal-weighted portfolio returns during the one-month period after the portfolio formation. Jensen alpha and the corresponding *t*-stat of each decile portfolio are estimated with respect to Carhart four-factor model.

Panel A: Performance of equally-weighted,sorted by bad MNA sensitivity

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	0.64	-0.06	-0.31	1.16	0.09	0.63	-0.52	-0.15	-1.19
2	0.78	0.13	1.31	1.04	0.13	1.75	-0.26	-0.00	-0.06
3	0.92	0.27	3.10	0.96	0.12	1.82	-0.05	0.15	2.69
4	0.85	0.20	2.53	0.96	0.15	2.37	-0.11	0.06	1.10
5	0.92	0.28	3.35	0.90	0.10	1.61	0.02	0.18	3.29
6	0.93	0.28	3.36	0.91	0.11	1.78	0.01	0.17	3.14
7	1.02	0.33	3.91	1.00	0.17	2.58	0.02	0.16	3.02
8	1.03	0.30	3.31	1.00	0.13	1.87	0.02	0.17	2.92
9	1.12	0.32	3.32	1.09	0.14	1.82	0.03	0.19	3.02
10	1.11	0.22	1.54	1.15	0.06	0.55	-0.04	0.16	1.77
.									
High-Low	0.47	0.28	1.16	-0.00	-0.03	-0.15	0.47	0.30	1.99
9-2	0.34	0.19	1.29	0.05	0.00	0.02	0.29	0.19	1.98

Panel B: Characteristics of equally-weighted portfolios sorted by bad MNA sensitivity

	pre-formation			post-formation					
Portfolio	β_{bad}	β_{good}	β_{MKT}	β_{bad}	β_{good}	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-3.18	-0.24	1.37	-0.13	0.08	1.20	0.83	-0.22	-0.30
2	-1.45	-0.19	1.14	-0.10	-0.17	1.03	0.59	0.02	-0.16
3	-0.85	-0.16	1.05	-0.04	-0.13	0.96	0.51	0.11	-0.08
4	-0.44	-0.14	1.01	-0.06	-0.15	0.94	0.44	0.18	-0.05
5	-0.11	-0.10	1.00	-0.04	-0.21	0.92	0.42	0.19	-0.02
6	0.21	-0.08	1.00	-0.01	-0.18	0.93	0.39	0.21	-0.02
7	0.55	-0.06	1.02	0.03	-0.09	0.96	0.44	0.26	-0.00
8	0.95	-0.04	1.06	0.05	-0.18	1.00	0.47	0.27	-0.00
9	1.51	-0.08	1.13	0.09	-0.08	1.08	0.56	0.30	0.00
10	3.15	-0.03	1.29	0.15	0.01	1.22	0.78	0.15	-0.02

Table 12: Continued

Panel C: Performance of equally-weighted portfolios sorted by good MNA sensitivity

	Full month			MNA days			Non-MNA days		
Portfolio	Ret	Alpha	t-stat	Ret	Alpha	t-stat	Ret	Alpha	t-stat
1	1.13	0.29	2.37	1.11	0.07	0.74	0.01	0.22	2.76
2	1.09	0.34	4.06	1.12	0.19	2.92	-0.03	0.15	2.85
3	1.04	0.33	4.25	1.06	0.19	3.17	-0.03	0.14	2.85
4	1.03	0.36	4.60	1.02	0.19	3.15	0.01	0.17	3.44
5	0.89	0.25	3.14	0.99	0.19	3.00	-0.10	0.07	1.32
6	0.93	0.28	3.56	0.96	0.15	2.57	-0.03	0.13	2.48
7	0.99	0.33	4.02	1.01	0.18	2.87	-0.02	0.15	2.84
8	0.85	0.20	2.39	0.95	0.11	1.72	-0.10	0.09	1.68
9	0.85	0.17	1.83	0.92	0.03	0.49	-0.07	0.13	2.35
10	0.66	-0.09	-0.68	1.03	-0.00	-0.02	-0.36	-0.08	-1.00
.									
High-Low	-0.46	-0.38	-2.17	-0.09	-0.07	-0.54	-0.38	-0.31	-2.65
9-2	-0.24	-0.17	-1.48	-0.21	-0.16	-1.74	-0.03	-0.02	-0.25

Panel D: Characteristics of equally-weighted portfolios sorted by good MNA sensitivity

	pre-formation			post-formation					
Portfolio	Good	Bad	β_{MKT}	Good	Bad	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}
1	-3.11	-0.14	1.26	-0.01	-0.04	1.14	0.78	0.21	-0.10
2	-1.46	-0.05	1.12	-0.12	-0.04	1.04	0.58	0.26	-0.08
3	-0.93	0.02	1.06	-0.17	-0.05	0.99	0.49	0.26	-0.06
4	-0.56	0.03	1.02	-0.17	-0.03	0.94	0.46	0.23	-0.05
5	-0.24	0.04	1.01	-0.20	-0.06	0.93	0.41	0.19	-0.04
6	0.06	0.06	1.00	-0.12	-0.03	0.93	0.40	0.20	-0.03
7	0.37	0.11	1.01	-0.14	-0.02	0.95	0.44	0.20	-0.04
8	0.74	0.09	1.04	-0.06	0.01	0.98	0.44	0.14	-0.05
9	1.25	0.10	1.10	-0.15	0.07	1.03	0.48	0.11	-0.05
10	2.82	0.11	1.29	-0.03	0.09	1.18	0.72	-0.08	-0.14

Chapter 2

Firm and Country Determinants of Firm Betas and Contagion

1 Introduction

There is a large and active literature modeling firm-level betas, both during normal and in stress times. There is also a continued interest in what characteristics make countries particularly exposed to disruptive foreign contagion. We combine both literatures and test using a sample of firm-level data from 54 countries what country and firm characteristics (and possibly their interactions) make firms particularly exposed (unexposed) to periods of market stress.

Our empirical strategy involves several steps. First, because we will differentiate between betas in normal and crisis times, we develop a new methodology to identify crisis periods first. We begin with the idea that crisis periods have persistently low equity returns and high equity market volatility, and typically start with a crash. We adopt an ordinal approach to transform these symptoms into a crisis indicator. We use the US market to calibrate the key model parameters. In particular, we set the parameters so that the US crisis incidence is close to the population incidence of the top volatility regime in a 3-state regime-switching volatility model (about 17%). We then impose the parameters calibrated on US data on the other markets. After applying the methodology to individual countries, we create global crisis indicators based on local ones. Specifically, we define a week as being in global crisis if more than 66% of all countries (or 75% of total market cap) experience a local crisis during that week. For the 75% market cap measure, we find about 8.5% of weeks to be global crisis weeks (with an average equity index return of -1.16%). The 66% of countries measure leads to a lower crisis incidence (4.86% of weeks) but a higher average weekly return impact (-1.91%).

In the second step, we build a predictive model for firm global and (orthogonalized) local equity market exposures in 'normal times', that is, outside crisis periods. We first measure yearly (July to June) realized global and local factor betas using the simple and robust estimation procedure recently proposed by Welch (2019). Subsequently, we relate next year's betas to a combination of past betas (measured at different frequencies, as in the Corsi (2009) volatility model) as well as firm and country characteristics. We estimate the prediction model for developed and developing countries separately. For developed markets, we find a strong relationship between future global betas and both the current one-year and particularly 5-year realized betas. While country characteristics capturing economic and financial openness have little to no predictive power for firm betas, we find a robust relationship with firm fundamentals such as size, stock liquidity, and idiosyncratic volatility. Surprisingly, we do not find firm betas to be associated with financial leverage. Results for developing market global betas are mostly similar, except for the strong positive relation between firm betas and country-level measures of *de jure* and *de facto* integration. We also build a prediction model for local betas, and confirm a strong relationship with past realized betas as well as with the same set of firm characteristics.

The final step then searches for the characteristics that make firms perform excessively poorly (well) during crisis times. Excessive here should be interpreted as worse (better) relative to what was to be expected given the predicted factor exposures. To empirically test this, we first calculate a firm's abnornal return as the difference between the firm's return and its predicted return (in turn calculated as the product of the predicted factor exposures and the factor returns). Subsequently, we test whether (1) the abnormal returns are significantly negative during crisis times (which would signal "contagion unrelated to the factors), (2 and 3) whether the abnormals returns tend to positively correlate with the global and local factors during stress times. Under the null of no global (local) factor contagion, we expect this correlation to be indistinguisable from zero. The main contribution of our paper is that we let these contagion exposures depend on (the interaction between) country and firm characteristics. More specifically, we develop and test 4 separate hypotheses (future versions will develop other hypotheses). Our first hypothesis tests the idea that quality stocks provide downside market protections as they may benefit from flight to quality during crises (see Asness et al. (2019)). We only find evidence for this hypothesis in developed markets, where firms with higher ROE and low earnings volatilty (a crude proxy for managerial quality) tend to be less prone to local and global factor contagion, respectively. High financial leverage is not robustly related to contagion exposures. Second, following Bekaert et al. (2014), we test the so-called wake-up call hypothesis, which states that when investors re-evaluate their positions in market downturns, countries with strong domestic macroeconomic fundamentals should be more insulated from contagion than countries with week fundamentals. Again, we find strong evidence for this channel, but only within developing markets. Our third hypothesis originates from the tendency of fire-sales during downturns documented by Ben-David et al. (2012). In particular, they show evidence that when confronted with large withdrawals, fund managers tend to first sell the largest and most liquid stocks, and stick to their positions in smaller illiquid stocks that they would otherwise have to sell at fire-sale prices. We therefore hypothesize that, at least initially, large and liquid firms should be more crisis-prone relative to smaller and less liquid ones, and that the effect should be increasing with de facto market integration (as reflected by e.g., a high level of foreign market participation). Our empirical findings for developed markets, however, direct to the opposite conclusion: large and liquid firms tend to be less crisis prone relative to smaller and less liquid firms. These findings are consistent with those in Baele et al. (2019) and indicate a flight to large and liquid stocks during stress times. In developing markets, however, we find global and local crisis exposures to be positively related to foreign equity market participation, and especially so for the more liquid firms. We also find strong contagion unrelated to the factors, but this contagion intensity seems largely unrelated to both country and firm characteristics. The fourth hypothesis is based on the literature showing that foreign banking crises may spill over to the local credit market either through the negative effect on the domestic banking system (via inter-banking market and surges in funding costs) or directly by reducing the amount of credit that foreign banks lend to local firms (see Ivashina and Scharfstein (2010), Schnabl (2012), Iyer et al. (2013), Ongena et al. (2015), and Degryse et al. (2019)). With worsening domestic credit conditions during crisis periods, it is straight-forward to expect more levered firms to be more exposed to contagion. Also, Giannetti and

Ongena (2009) show that foreign banks tend to lend to mainly large firms. Therefore, we expect a credit contraction shock should have a stronger impact on these firms. Furthermore, we expect the effect to be stronger in countries that have a higher reliance on foreign funding, and measure foreign credit dependence by total domestic borrowing from foreign banks relative to GDP. For developed markets, we do find larger contagion exposures in countries that borrow more from abroad, but not that these exposures depend on firm size. In developing markets, however, consistent with our hypothesis, we do find highly levered and large firms to be more exposed to contagion in countries that depend more on foreign credit.

This paper contributes to several streams in the literature. First, this paper contributes to the huge literature on international financial contagion, most of which focus on aggregate stock market indices. Calvo and Reinhart (1996) and Baig and Goldfajn (1999) find evidence of contagion during the 1994 Mexican peso crisis and Asia crisis. Forbes and Rigobon (2002) find that contagion evidence based on changes in cross-market correlations across normal and crisis periods can be biased by heteroscedasticity. Bae et al. (2003) propose a multinomial logistic regression approach to measure contagion. Bekaert et al. (2005a) and Bekaert et al. (2014) define contagion as "correlation over and above what one would expect from economic fundamentals." They use a factor model with time-varying betas to accommodate various degrees of market integration. More recently, the literature uses data on ownership or borrowing activity of individual companies to study shock transmission and contagion. With fund-level data, Jotikasthira et al. (2012) and Hau and Lai (2017) find that stock transactions induced by fund flow of mutual fund lead to significant price pressure on shares they owned, and cause shock transmission from developed countries to emerging markets or from financial stocks to non-financial stocks. Schnabl (2012), Iyer et al. (2013), Ongena et al. (2015) document transmission of bank funding shock across countries, with firms dependent on bank credit suffering the most.

Our study also relates to the research on stock performance during market downturns and normal times. Kapadia et al. (2018) show that stocks hedging bad times earn high average returns. Similarly, Gormsen and Greenwood (2017) show that firm with characteristics associated with good performance during bad times also perform well during good times. Ang et al. (2006), Kelly and Jiang (2014), Bali et al. (2014), Van Oordt and Zhou (2016), Chabi-Yo et al. (2018), and Atilgan et al. (2019) investigate individual stock exposures to extreme market downturns and test whether left-tail risk predicts cross-sectional variation in future stock returns. This paper differs from these studies as we focus not only on raw return performance but also on contagion, i.e. excess comovement over and above what is implied by exposures to global and local factors. Also, our study features an international dimension and study stocks from a large sample of countries.

Last, our paper also provides insightful results on the determinants of firm-level betas. Theoretically, Gomes et al. (2003), Carlson et al. (2004), and Zhang (2005) link market beta to size and book-to-market. Empirically, Brooks and Negro (2006) find that companies operate globally have higher exposures to global shocks. Cosemans et al. (2016) find a significant relation between beta and size, book-to-market, and leverage. In this paper, we build a beta prediction model including firm and country characteristics, past beta, and crisis incidence. Moreover, we test it using international stocks instead of only US stocks used by other studies.

2 Empirical Framework

The goal of our paper is to identify the firm and country characteristics that make firms particularly vulnerable to crisis periods. Below, we propose a two-factor model that decomposes firms' crisis sensitivities into multiple components. First of all, firms with higher exposures to global and/or local factor shocks are expected to be hit harder during crisis periods compared to firms with low exposures. We model firm betas as a function of past betas as well as country and firm characteristics in Section 2.2, hereby contributing to a large literature on how to optimally model and predict firm-level betas. A second reason for firms to be hit harder by crises is that their factor exposures may suddenly increase during crisis times. This 'excess' comovement, that is, comovement in excess of what is predicted by the baseline factor exposures, is often denoted as 'contagion' (see e.g., Bekaert et al. (2005b)). An alternative source of excess comovement is that all stocks with specific characteristics tend to drop in value, irrespective of their market exposures. Section 2.3 introduces the methodology to identify these different channels of excess comovement and develops a set of hypotheses that link country and firm fundamentals to excess contagion. We relegate the discussion of the empirical results to Section 3. Both to estimate firm betas in normal and stress times, we need to identify crisis periods. We therefore first develop and implement a new 'ordinal' crisis identification method in Section 2.1.

2.1 Identifying Crises Periods

There is no generally accepted definition of what constitutes a crisis period, and hence also no unified way of identifying such periods. In their paper, Kapadia et al. (2018) use the methodology by Pagan and Sossounov (2003) to identify downwards ('bear') markets. When we apply their measure to our US sample, we find that about 25% of weeks are identified as bear markets. On average, a downward spell takes 45 weeks, with a minimum of 14 and a maximum of 133 weeks. As can be seen from Figure 1, this method identifies longer spells of downward markets from top to bottom. Gormsen and Greenwood (2017) follow a simple three-step approach. First, they define *financial bad times* as quarters in which either the quarterly or the yearly US stock market excess return is in the bottom quintile of their sample. Second, they define a quarter to be *economic bad times* if at least one of its months is registered as a recession by the NBER. Finally, they set their quarterly 'rainy day' dummy equal to one if the quarter has both economic and financial bad times and zero otherwise. They describe their definition of bad times as 'restrictive', as it 'may leave out some periods that would be admitted as a bad time under some specifications', and directed at 'minimizing false positives. Not surprisingly then, over their 1963-2013 sample for the US, they only identify 7 spells; the number of spells in their 1986-2013 international sample is limited to 5.

In our view, not all crisis periods are necessarily part of a persistent downward market or recession period. A good example is the 1987 crash, which is not characterized as a crisis period by the Gormsen and Greenwood (2017) methodology. Similarly, not all weeks within a downturn should necessarily be characterized as crisis weeks. For instance, as Figure 1 illustrates, downward market spells are frequently interrupted by (temporary) recovery periods. In what follows, we develop a new crisis identification methodology that allows for a more detailed crisis identification at the weekly frequency.

2.1.1 An Ordinal Crisis Model

Two key symptoms of crisis periods are persistently low equity returns and high equity market volatility. We now develop an ordinal approach that transforms these two symptoms into a crisis indicator. Let $r_{c,t,K}$ be the cumulative return between time t and $t+K$ for country c:

$$r_{c,t,K} = \prod_{k=0}^{K} \left(1 + r_{c,t+k}\right) - 1$$

At each point in time $t = 1..T-K$, we calculate forward cumulative returns over horizons $K = 5, 13, 26, 52$ weeks, that is, approximately, over the next 1, 3, 6, and 12 months. Similarly, we calculate realized volatility $\sigma_{c,t,K}$ over the same set of horizons, that is, the realized volatility of daily returns over the next 5, 13, 26, and 52 weeks. To increase the accuracy of our volatility estimates, we use daily rather than weekly returns. Subsequently, we transform the cumulative return (forward realized volatility) series into an ordinal indicator by replacing each observation by its ranking (in descending order for cumulative returns, in ascending order for realized volatility) over the sample period, normalized by the total number of observations; values closer to one (zero) are therefore associated with a lower (higher) future cumulative return and higher (lower) future realized volatility. We stack the 4 ordinal series for the forward returns and volatilities in $T \times 4$ matrices OI_{fr} and $OI_{f\sigma}$, respectively. Finally, as we will need it to decide whether the current weekly return initiates a new crisis period, we use a similar procedure to transform the weekly returns into a vector of ordinal numbers OI_r (ranking from high to low, so that extreme negative returns are associated with ordinal numbers close to 1). With those ordinal numbers in hand, we categorize a weekly observation t as a crisis if:

1. The ordinal number of that week is larger than a crisis trigger threshold level, i.e. $OI_{r,t} \geq Tr$,

and at least one of the 8 ordinal numbers for future returns/volatilities is larger than some threshold level Thr_f.

2. The previous week was categorized as a crisis week, and at least one of the 8 ordinal numbers for future returns/volatilities is larger than some threshold level Thr_f.

As is also the case for other crisis identification methods, our crisis measure will ultimately depend on the chosen value of some key parameters. In our model, these are the crisis trigger level Tr and crisis threshold level for the forward returns/volatilities Thr_f. Also slight changes to the model (e.g. only taking into account forward returns, or requiring both the forward return / volatility ordinal numbers to be above the threshold) could change crisis identification. Given that plenty of validation statistics are available for it, we propose to first validate our measure for the US market. We then impose the 'optimal' model / set of parameters to the other countries.

It is our intention for future versions to actually 'fit' our model to a large set of US crisis indicators. We will not only fit our model to standard crisis indicators, but also to a self-created text-based crisis indicator. Our current approach is simpler and only serves as a first step. First, it is our prior that crisis incidence should be somewhere in between 2-3 percent (the incidence of FTS in Baele et al. (2019)) and 25 percent (the percentage of bear market weeks according to the Pagan and Sossounov (2003) measure). At the same time, crisis periods should be somewhat persistent (but not as persistent as bear markets). Second, the population incidence of the highest volatility regime in a 3-state regime-switching model may serve as an anchor. That probability estimated for the US over our sample is 17.87%. Finally, we compare values of various sentiment and real indicators between crisis and non-crisis periods. We would expect sentiment and real indicators of our measure to be worse relative to the more conservative bear market measure of Pagan and Sossounov (2003).

We summarize the main findings of this calibration exercise here; detailed results are available upon request in a separate document. To simplify the analysis, we impose $Tr = Thr_f$. Not surprisingly, we find crisis incidence and persistence to decrease with the threshold levels. Incidence decreases from nearly 30% for a threshold level of 0.80 to less than 5% when the threshold is set at

0.95. Crisis incidence is close the population incidence of the top (of 3) volatility regime of 17.87% when we set the threshold level to 0.875. Figure 2 compares crisis incidence for this threshold level generated from a model that takes only future returns into account (Panel A) and the full model that incorporates both future returns and volatilities (Panel B). As is more generally the case, incidence is lower for the return-only (15%) compared to the full (18%) measure. Spells are generally less frequent but more persistent when volatility is also used in the crisis identification process. The return-only measure generates some very short crisis periods that may be too brief to be properly characterized as crises. For that reason, in what follows, we use the full measure using a threshold level of 0.875.

During our identified crisis periods, we find the levels of realized volatility, the VIX, the TED spread, as well as term structure noise measure of Hu et al. (2012) to be substantially higher compared to during normal times and relative to the values during downward markets as identified by the Pagan and Sossounov (2003) measure. Similarly, we find US Treasury Bonds and safe haven currencies (Japanese Yen, Swiss Frank, US Dollar) to appreciate during crisis times. Real economic indicators, such as the Chicago Fed National Activity Index as well industrial production, on the other hand, decrease substantially.

2.1.2 Application to other markets

We subsequently identify crisis periods in other countries by setting the trigger and threshold parameters in our full model equal to 0.875. The first columns of Table 1 report local crisis incidence and return impact for developed (Panel A) and developing markets (Panel B). Median crisis incidence across developed countries equals 16.9%, with a tight interquartile range (IQR) of [16.0%; 18.9%]. During a crisis period, the weekly developed market returns are on average -0.71% with an IQR of [-0.89%; -0.60%]. Crisis incidence is the lowest in Switzerland (13%) and highest in France (22.5%). Panel B shows that both median crisis incidence (18.4%, with IQR of [16.8% - 19.8%]) and return impact (0.80%, with IQR of [-0.94% -0.55%]) are slightly higher for developing markets.

Based on the individual crisis measures, we create two global crisis indicators. Our first global crisis indicator is 'on' if at least 66% of all countries (with equal weights) experience a crisis. Our second 'value-weighted' indicator defines a global crisis as a week during which at least 75% of market cap suffers a local crisis. De facto, this means that the US and several other (large) markets must experience a crisis at the same time. Apart from global crisis indicators, we also construct developed and developing country crisis indicators by aggregating within developed or developing countries only.

Columns 3-6 of Panel A show that median global crisis incidence is lower for the equally (4.86%) compared to the value-weighted (8.5%) measure, that is, the requirement that at least 2 out 3 countries must be in crisis is a more stringent requirement than the 75% market cap threshold. Both measures are substantially below the median local crisis incidence of 16.9%, suggesting that a large fraction of local crisis events are country-specific. Median return impact is substantially higher during global (EW: -1.91%; VW: -1.16%) compared to during local (-0.71%) crises, especially for the more demanding equally-weighted measure. The corresponding columns in Panel B show that both crisis incidence and return impact are similar albeit slightly higher for emerging markets. The final columns of both panels report summary statistics for the developed and developing markets specific crisis indicators. Developed market crisis incidence (Panel A) is only moderately higher (EW: 7.11%, VW: 10.94%) compared to global crisis incidence (EW: 4.86%, VW: 8.49%), indicating that a large proportion of developed-market-specific crisis is global in nature. For emerging markets, as the standard threshold of 75% proved too stringent (less than 3% crisis incidence), we set the market-cap threshold to 50%. The median developed market crisis incidence then amounts to 5.16% for the equally-weighted and 11.2% for the value-weighted measure.

2.2 Predicting Firm-Level Factor Exposures

The first reason why stocks may be hit differently by crises is that their expected factor exposures (or 'betas') are different, with high beta stocks expected to be more affected relative to low beta stocks. As in Bekaert et al. (2014), we distinguish between a global and a domestic equity market factor, that is, stocks comove because they are jointly exposed to both global and local equity market shocks[1]. As domestic markets are likely highly influenced by global market events, in Section 2.2.1, we first orthogonalize the local to the global market returns. Subsequently, in Section 2.2.2, we develop a predictive model for realized global and local firm betas in normal times. This section discusses the empirical strategy only; empirical results are relegated to Section 3.2.

2.2.1 Identification of pure local market shocks

One common way to orthogonalize local to global market shocks is to just take the residual from a regression of local on global market shocks. This approach implicitly assumes a constant global market beta for local market returns. Evidence in Baele and Inghelbrecht (2010), however, shows that global market betas fluctuate both over the cycle and with measures of economic and financial openness. To acknowledge this time variation in global market betas, we proceed in several steps. First, we estimate for every July to June period the yearly realized beta by regressing the weekly excess local returns over that period on the corresponding global returns. Second, we predict the global beta for country j in year $t+1$ using the following model:

$$\begin{aligned} \beta^{w}_{j,t+1} &= \alpha + \gamma_1 \times \beta^{w}_{j,t} + \gamma_2 \times \beta^{w\,(5)}_{j,t} + \gamma_3 \times X_{j,t} \\ &\quad + \gamma_4 \times CR_{t+1} + \gamma_5 \times CR_t + \gamma_6 \times CR^{(5)}_t + \varepsilon_{j,t+1} \\ \beta^{w\,(5)}_{j,t} &= \frac{1}{5}\sum_{h=1}^{5} \beta^{w}_{j,t-h+1},\ CR^{(5)}_t = \frac{1}{5}\sum_{h=1}^{5} CR_{t-h+1} \end{aligned} \tag{1}$$

Similar in spirit to Corsi (2009)'s volatility prediction model, we make country j's next year's global beta $\beta^{w}_{j,t+1}$ a function of the country's realized 1-year ($\beta^{w}_{j,t}$) and 5-year ($\beta^{w\,(5)}_{j,t}$) betas measured at time t. We additionally include a set of country indicators $X_{j,t}$ to capture the effect of time-varying economic and financial openness and of the economic cycle on global betas. As we want to predict market betas in normal times (that is, outside crisis periods), we also need to control for the potential effect of crisis periods on market betas (previous research suggests betas increase

[1]Future versions may also consider other equity factors, such as the Fama-French size and value factors.

during stress periods). We therefore also include the percentage of crisis weeks within the current and past year, as well as over the last 5 years. Third, we use the estimates in this model to predict next year's market beta $\hat{\beta}^{w}_{j,t+1}$, assuming that no crisis is expected for the next year, that is, in our prediction models, we set $CR_{t+1} = 0$. Finally, we calculate the pure country return shock $\widetilde{r}_{j,\tau}$ for week τ in year $t+1$ by subtracting $\hat{\beta}^{w}_{j,t+1}$ times the global market return $\widetilde{r}_{j,\tau}$ for that week from the local market return.

2.2.2 Predicting firm-level betas in normal times

To estimate firm level global and local market betas, we regress on a yearly basis (year t, from July to June) firm i's return during week τ on global factor $r_{world,\tau}$ and local factor $\hat{r}_{j,\tau}$:

$$r_{i,\tau} = \alpha_{i,t} + \beta^{w}_{i,t} \times r_{world,\tau} + \beta^{l}_{i,t} \times \hat{r}_{j,\tau} + \varepsilon_{i,\tau} \tag{2}$$

As realized betas tend to be rather noisy and unstable, we use the robust one-pass estimator recently introduced by Welch (2019). More specifically, instead of estimating equation (2) on the raw firm return $r_{i,\tau}$, we estimate it on the return winsorized to $[r_{j,\tau} - 10\%,\ r_{j,\tau} + 10\%]$, that is, 10% below or above the local market return. Welch (2019) shows that betas estimated following this procedure predict future realized betas better than prominent market-beta estimators, including the Vasicek (1973) model which is much more difficult to implement.

Subsequently, we estimate the following panel model to predict firm global betas over time:

$$\hat{\beta}^{w}_{i,t+1} = \alpha + \eta_1 \hat{\beta}^{w}_{i,t} + \eta_2 \hat{\beta}^{w\ (5)}_{i,t} + \eta_3 \hat{\beta}^{w}_{j(i),t} + \eta_4 \hat{\beta}^{w\ (5)}_{j(i),t} \tag{3}$$

$$+ \eta^{w}_{5} \times X_{j,t} + \eta^{w}_{6} \times Z_{i,t} \tag{4}$$

$$+ \eta^{w}_{7} \times CR_{t+1} + \eta^{w}_{8} \times CR_{t} + \eta^{w}_{9} \times CR^{(5)}_{t} + \varepsilon_{i,\tau}.$$

Similar to the country beta model, we predict each firm's next year's beta using its current 1 year and 5 year global beta ('Corsi Model'). We also include the 1 and 5-year global betas of the country in which the firm is located, a number of country characteristics $X_{j,t}$ to capture the potential effect of time-varying economic and financial openness and changing economic conditions on firm betas, as well as the proportion of crisis weeks during the current and past 1 and 5 years. We additionally make firm level betas a function of a set of lagged firm characteristics $Z_{i,t}$. Following Cosemans et al. (2016), we include firm size, book-to-market, and financial leverage as firm characteristics. We additionally include measures of a stock's liquidity (percentage of nonzero returns over last year), idiosyncratic volatility (the standard deviation of the residual in equation (2), as well as the firm's Altman Z-score and Gross Profit. To facilitate the (economic) interpretation of the parameter estimates, we (cross-sectionally) standardize all firm characteristics within developed countries and developing countries, respectively. We build a similar prediction model for local betas; only we remove country characteristics and replace global crises by local crises.

Finally, we use the estimates in this model to predict next year's global and local beta $\hat{\beta}^{w}_{i,t+1}$ and $\hat{\beta}^{l}_{i,t+1}$, assuming that no crisis is expected for the next year, that is, in our prediction models, we set $CR_{t+1} = 0$

2.3 Modelling Excess Comovement

The main goal of this paper is to identify the characteristics of firms that perform particularly badly during crisis times, that is, worse than one would expect given their normal factor exposures. In Section 2.3.1, we first outline our test for excess comovement. In Section 2.3.2, we develop the hypotheses that link country and firm characteristics to excess comovement.

2.3.1 A Test for Excess Comovement

To study return comovement over and above the predicted exposures to global and local factors, we first calculate abnormal stock returns:

$$abret_{i,\tau} \equiv r_{i,\tau} - \hat{\beta}^{w}_{i,t} \times r_{world,\tau} - \hat{\beta}^{l}_{i,t} \times \hat{r}_{j,\tau}. \qquad (5)$$

Under the null hypothesis that our factor model is correctly specified, one would expect these abnormal returns to be uncorrelated with firm or country characteristics, factor returns, crisis dummies, and all their interactions. To test this hypothesis, we estimate the following panel model:

$$
\begin{aligned}
abret_{i,\tau} = {} & \alpha + \gamma_1 Z_{i,t-1} + \gamma_2 X_{j,t-1} + \gamma_3 X_{j,t-1} Z_{i,t-1} \\
& + (\gamma_4 + \gamma_5 Z_{i,t-1} + \gamma_6 X_{j,t-1}) \times r_{world,\tau} \\
& + (\gamma_7 + \gamma_8 Z_{i,t-1} + \gamma_9 X_{j,t-1}) \times \hat{r}_{j,\tau} \\
& + (\gamma_{10} + \gamma_{11} Z_{i,t-1} + \gamma_{12} X_{j,t-1} + \gamma_{13} Z_{i,t-1} X_{j,t-1}) \times Crisis_\tau \\
& + (\gamma_{14} + \gamma_{15} Z_{i,t-1} + \gamma_{16} X_{j,t-1} + \gamma_{17} Z_{i,t-1} X_{j,t-1}) \times r_{world,\tau} \times Crisis_\tau \\
& + (\gamma_{18} + \gamma_{19} Z_{i,t-1} + \gamma_{20} X_{j,t-1} + \gamma_{21} Z_{i,t-1} X_{j,t-1}) \times \hat{r}_{j,\tau} \times Crisis_\tau \\
& + \varepsilon_{i,\tau}
\end{aligned}
\tag{6}
$$

First of all, we relate abnormal returns to both firm ($Z_{j,t}$) and country ($X_{j,t}$) characteristics. We expect especially many elements of parameter vector γ_1 to be significant, as they capture the tendency of certain firm characteristics (e.g. size, book-to-market, ROE, leverage) to be associated with higher returns. In principle, even if we do not have clear hypotheses for this channel right now, it may be that the pricing of these firm characteristics interacts with country characteristics, which would be captured by parameter γ_3. Second, we may be systematically under- or overestimating the global and local betas of firms (effect captured by γ_4 and γ_7), and this bias may depend on firm (captured byγ_5 and γ_8) and country (captured by γ_6 and γ_9) characteristics. Finally, we test for three sources of excess comovement during crisis times, each potentially dependent on (a combination of) firm and country fundamentals:

1. Excess comovement unrelated to the factors, captured by γ_{10} to γ_{13}.

2. Excess comovement with respect to the global factor, captured by γ_{14} to γ_{17}.

3. Excess comovement with respect to the local factor, captured by γ_{18} to γ_{21}.

To prevent a proliferation of parameters, we restrict ourselves to those combinations of firm and country characteristics for which clear hypotheses can be proposed. We discuss those in the next section.

2.3.2 Hypothesis Development

Hypothesis I: Top quality firms are less crisis-prone compared to firms with lower quality characteristics. Our first hypothesis states that firms with quality characteristics should be relatively insulated from disruptive crises. Quality is a broad term that includes low leverage, high profitability, stable earnings, top quality management, and high (stock) liquidity. To the extent that there is a flight to quality and/or liquidity within the stock market, we would expect high quality stocks to outperform stocks with lower quality characteristics. Baele et al. (2019) in fact document for a large sample of international equities that flights-to-safety are as much flights to quality as they are flights to liquidity. Both Kapadia et al. (2018) and Gormsen and Greenwood (2017) shows that more profitable and liquid firms tend to outperform unprofitable and illiquid ones during market downturns. Kapadia et al. (2018) furthermore document highly levered firms to perform worse during bear markets. In what follows, we will use Financial Leverage, Altman's Z-Score, Return on Equity (ROE), and stability of earnings (proxies by the 5-year trailing standard deviation in earnings) as quality proxies.

Hypothesis II: Countries with weaker domestic macroeconomic fundamentals are more vulnerable to contagion Bekaert et al. (2014) show that high current account deficits or low foreign exchange reserves make countries more vulnerable to contagion. This is consistent with a wake-up call hypothesis where a crisis leads investors to re-examine their positions and exit countries with poor fundamentals. Following the measures from Bekaert et al. (2014), we hypothesize that markets with a high current account deficit, high government budget deficit, high unemployment, low sovereign credit rating, and low foreign exchange reserves are more vulnerable to contagion.

The next hypotheses involve the interaction between country and firm characteristics.

Hypothesis III: Large and liquid firms are more exposed to contagion, especially in financially integrated markets. Foreign investors tend to have a preference for large and liquid firms (see e.g., Kang and Stulz (1997) and Dahlquist and Robertsson (2001)) located in financially developed equity markets. When confronted with large withdrawals, fund managers often tend to first sell the largest and most liquid stocks, and stick to their positions in smaller illiquid stocks that they would otherwise have to sell at fire-sale prices (see Ben-David et al. (2012)). We therefore hypothesize that, at least initially, large and liquid firms should be more crisis-prone relative to smaller and less liquid ones, and the effect should be increasing with de facto market integration (as reflected by e.g., a high level of foreign market participation).

Hypothesis IV: Highly levered firms are more exposed to contagion, especially in countries highly dependent on foreign credit.

Foreign banking crises may spill over to the local credit market either through the negative effect on the domestic banking system (via inter-banking market and surges in funding costs) or directly by reducing the amount of credit that foreign banks lend to local firms. To the extent that crises periods are associated with worsening domestic credit conditions, we expect more levered firms to be more exposed to contagion. Also, given the tendency of foreign banks to lend to mainly large firms (see Giannetti and Ongena (2009)), a credit contraction shock should have a stronger impact on these firms. Furthermore, we expect the effect to be stronger in countries that have a higher reliance on foreign funding, and measure foreign credit dependence by total domestic borrowing from foreign banks relative to GDP.

3 Empirical Results

3.1 Sample Construction

We collect data on individual stock returns and firm characteristics for 24 developed and 30 developing countries over the period July 1981 to December 2018. Our initial set of stocks contains all firms, both active and inactive, covered by Worldscope. Following Griffin et al. (2010), we only include common stocks[2] that trade on major stock exchanges[3] and are the main issue of their firm. This first set of filters reduces the number of stocks from 82,620 to 54,297. Excluding financial firms reduces the sample further to 42,665 firms. Subsequently, we collect daily and weekly total returns (both in USD and local currency) from Datastream for each of these 42,665 firms. Dropping firms that have no return data reduces the sample further to 42151 stocks. We require a stock to have at least 52 weekly return observations. We set weekly returns as missing if the return index that week is equal or below 0.01. Within each country, we winsorize weekly returns at the 99.9 percentile. For our liquidity screen, we download daily returns (in local currency) and calculate for each stock the percentage of zero daily returns over the previous year (June to June) (see e.g., Lesmond et al. (1999) and Bekaert et al. (2007)). We drop the entire year of weekly returns of firms that had a proportion of zero daily returns more than 75% in the previous year. Our final sample includes 39,432 (25,988 from Developed Markets; 13,444 from Emerging Markets). The first columns of Table 2 report per country the year from which each country is included, as well as the total and average number of stocks per country, both for Developed Markets (Panel A) and Emerging Markets (Panel B). Most developed countries enter the sample from 1981. Data coverage on emerging market stocks starts mostly in the late 1980s or early 1990s. Therefore, our sample on emerging markets starts from 1989 July.

Subsequently, we download for each stock the accounting variables necessary to calculate the firm characteristics listed in Appendix A[4]. To minimize data errors in Worldscope, we employ the following procedure. We set the values of total debt, cash holding, total asset to be missing if they are negative. Next, we wonsorize them and earnings per share volatility at the top 99.5%. Other firm characteristics including gross profit, ROE, and BE/ME winsorized on both bottom and top at 0.5% and 99.5%. Z-score from Altman et al. (2017) is calculated using winsorized firm characteristics. Columns 4 and following of Table 2 report for each indicator the percentage of firm-

[2]This de facto removes all preferred stocks, warrants, REITs, closed-end funds, exchange-traded funds, and depository receipts.

[3]While for most countries there is a single 'main' stock exchange, we include stocks from two exchanges in China (Shanghai Stock Exchange and Shenzhen Stock Exchange) and Japan (Tokyo Stock Exchange and Osaka Securities Exchange) and three in the US (Amex, NYSE, and Nasdaq).

[4]We calculate Altman Z-score by ourselves, according to the Z" model in Altman et al. (2017).

week observations that have non-missing values for each firm characteristics. Across countries, we find the Czech Republic, Cyprus, and Israel to be more affected by missing values.

Table 3 presents summary statistics of weekly returns (denominated in US dollars) and firm characteristics (either as ratio or denominated in US dollars) for the final sample. The first four columns show time-series means of the weekly returns on (1) Datastream's Total Market Index (matched to our sample period), the (2) value-weighted and (3) equally weighted returns, and finally also of (4) the median returns. The average value-weighted return over our sample is very close to the average return on Datastream's Total market indices, despite that our sample excludes financial companies. The average equally-weighted returns are higher in nearly all countries, suggesting a strong small firm effect is at work. Surprisingly, the average median return is negative across most countries. The rest columns are time-series mean of median firm characteristics within each country. There is considerable cross-country variation in all firm characteristics, and the magnitudes and cross-sectional patterns are in large consistent with Hou et al. (2011).

We obtain data on country openness indicators and macroeconomic fundamentals from IMF, Oxford Economics, and BIS. We consider three types of country-level exposure: stock market de jure openness, de factor openness, and dependence on foreign credit. For de jure openness, we use capital control measure on equity from Fernández et al. (2016) based on IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). It is on a [0, 1] scale with one meaning total openness. We refer to it as Schindler index as the methodology is created by Schindler (2009). We use the size of the trade sector (exports plus imports) relative to GDP as a measure of economic openness. Baele (2005); Bekaert et al. (2005a) find that trade integration increases exposures of country stock returns to the global or regional equity market. To measure de facto equity market openness, we use foreign assets and liabilities of portfolio equity scaled by GDP following Lane and Milesi-Ferretti (2007) and Bekaert et al. (2016). As for dependence on foreign credit, we use total borrowing from foreign banks as a percentage of GDP from BIS Consolidated Banking Statistics, as well as cross-boarder borrowing by domestic banks and non-banks from BIS Locational Banking Statistics. Table 4 reports the data coverage of country indicators.

3.2 Country and Firm-Level Betas

3.2.1 Predicting country level beta

As discussed in Section 2.2.1, we orthogonalize local to global equity market returns by subtracting from the local return the global return times its predicted yearly global market beta. Table 5 reports estimation results for the predictive model for realized global market betas (equation (1) in Section 2.2.1). Panel A and B report results for developed and developing markets, respectively. As results are robust to using developed/developing market-specific crisis indicators, we only report results for the model using the global crisis indicator. We do distinguish between the equally-weighted global crisis measure, which requires at least 66% of countries to be in a crisis, and the value-weighted measure, which requires at least 75% of market cap to be in a crisis state. Both for developed (Panel A) and developing (Panel B) markets, we find next year's betas to be significantly related to both the one and 5-year realized betas. For developed markets, the weight is predominantly on the 5-year beta (slope coefficient of about 0.50, compared to 0.13 for the 1-year betas); for developed markets, past 1 and 5-year betas get relatively similar weights. The three integration measures (Schindler's index of de facto equity market integration, the ratio of foreign assets and liabilities of portfolio equity scaled by GDP, and trade openness), as well as the cyclical indicator (detrended OECD leading indicator) seem to add little in terms of explanatory power for developed market betas. For developing markets, however, we do notice a slight increase in R^2 when these 4 country characteristics are added. In particular, global betas tend to be higher in countries with higher levels of foreign equity ownership. Contrary to our expectations, developing countries' global market betas seem to negatively related to trade integration; the effect is, however, only marginally significant at best. Current crisis intensity is positive and significant for developed market betas, while the 1-year lagged crisis intensity is negative (but mostly not significant), indicating that betas tend to increase during crisis periods. The lagged 5-year crisis intensity is, however, somewhat surprisingly positive and significant. For developing markets, we find crisis intensities to be mostly insignificant.

Given the little additional explanatory power of country fundamentals for global betas, in what follows, we will use the parsimonious Corsi model (augmented with contemporaneous and lagged global crisis incidence) to predict the different countries' global market betas, and subsequently, to calculate the orthogonalized country shocks (assuming no crisis is expected for the next year, i.e. $CR_{t+1} = 0$).

3.2.2 Predicting firm level beta

Table 6 reports detailed estimation results for the firm-level global (Panel A) and local (Panel B) beta prediction model outlined in Section 2.2.2. The first two columns report results for developed markets; the last two for developing markets. Firm betas in developed markets are significantly related to both past 1-year and 5-year realized betas. The past global betas of the country firms belong to have about equal weights as the firms' own past betas. Firm betas tend to be lower rather than higher during crisis intense periods. While country characteristics are not robustly related to firms' global market exposures, plenty of firm characteristics are. To facilitate the economic interpretation of the parameter estimates, all country and firm characteristics are standardized within developed and developing countries, respectively. We confirm previous evidence that global betas are higher for larger and more liquid firms. Our finding that a firm's idiosyncratic volatility is strongly correlated with the firm's global beta confirms recent results by Liu et al. (2018); in fact, in economic terms, in our data, it is the most important determinant. The effect of leverage on betas is positive but never significant; a higher Z-score is associated with higher not lower betas (even though in economic terms the effect is small). Finally, more profitable firms, as measured by the Gross Profits to Total Assets ratio, tend to have slightly lower global market betas. Overall, for global beta our model leads to a R^2 of 31%, suggesting that a parsimonious Corsi model combined with firm characteristics leads to a reasonable prediction outcome.

The final two columns of the same table report results for developing markets. The explanatory power of the model for developing countries betas is much lower, with R^2 equal to 18%. With regard to local betas, we also observe a lower R^2 of 13% in developed countries compared to the case of global betas. For emerging markets, the R^2 of local beta prediction is 19%, similar to the global beta counterpart. We will conduct a out-of-sample test of the prediction model in the future version. Note that to mitigate the concern for model misspecification, we use γ_4 to γ_9 in Equation 6 to capture the bias related to country and firm characteristics. Firm betas are mostly related to the 5-year lagged firm beta; no robust relationship is found to past one-year realized betas. Betas also seem mostly unrelated to current or past crisis incidence. We do find betas to increase with our two measures of *de jure* (Schindler index) and *de facto* (ratio of foreign assets and liabilities of portfolio equity scaled by GDP) integration. Similar to our findings for developed markets, we find that firm betas increase with firm size, liquidity (of its stock), and idiosyncratic volatility, but tend to be unrelated to leverage and Z-score. What is different though is that we find a significantly positive relationship between a firm's beta and its book-to-market ratio, and that more profitable developed market firms tend to have larger not smaller betas.

Panel B of Table 6 reports estimation results for the local beta model, using the local rather than the global crisis indicator. As before, the 5-year realized beta turns out to be a more robust predictor of local betas compared to 1-year realized betas. We find mostly similar relationships with respect to firm characteristics.

Based on the estimated coefficients, we obtain predicted firm-level global and local beta $\hat{\beta}^{w}_{i,t+1}$ and $\hat{\beta}^{l}_{i,t+1}$ assuming again that no crisis is expected, that is $CR_{t+1} = 0$.

3.3 Excess Comovement Results

The abnormal returns during crisis times calculated following Equation (5) are summarized in Table 7. The first column reports for each country the average of weekly abnormal returns across stocks during value-weighted global crisis. Across countries, the median is -0.10% with a wide interquartile range [-0.24%, 0.02%]. Column 2 and 3 reports the average correlation between abnormal returns and global/local factors for each country. The median is around -0.07, with a relatively tight interquartile range [-0.1,-0.05] and [-0.13, -0.05]. The rest columns of Panel A as well as Panel B report similar results for equal-weighted global crisis and developing countries. They suggest that different markets have limited variation in the average correlation between abnormal returns and factors.

Next, we test for excess comovement during stress times using the framework outlined in Section 2.3.1. In our discussion, we follow the order of hypotheses as in Section 2.3.2, with a separate table for each hypothesis. Across all tables, Panels A and B report results for developed and developing markets, respectively. Similarly, the left and right hand sides of each table reports results involving the value-weighted and equally-weighted crisis indicators, respectively. To further keep the size of the tables manageable, we only report parameter estimates for terms involving crisis dummies. Results on non-interacted terms will be relegated to an online appendix.

In Table 8, we test our **hypothesis I** which states that high quality firms should be less exposed to contagion. Panel A shows that at least for developed countries there is little evidence that quality characteristics determine contagion exposures. We do find that global factor exposures tend to increase during crisis periods with leverage; the effect is, however, small in magnitude and only significant at the 10% level when the equally-weighted crisis indicator is used. Unrelated to firm characteristics, we find comovement with the local factors to decrease during stress times (a "negative local contagion effect"). On the other hand, consistent with contagion, we do find that, unrelated to the factors, firm value drops about 20 bps more than expected given factor exposures during crisis times. Panel B shows that, for developing markets, there is a considerable degree of heterogeneity in contagion exposures across firms. More profitable firms (as measured by their ROE) tend to have lower local crisis exposures during crisis times compared to less profitable firms. Global crisis exposures tend to be higher for firms with high volatility in earnings (per share), a (crude) measure of management quality. Contrary to our expectations, however, global factor exposures during crisis times tend to decrease (increase) with leverage (Altman's Z-score).

Table 9 tests for the wake-up call hypothesis **(hypothesis II)** which states that firms in countries with weaker fundamentals should be hit harder by contagion. As can be seen from Panel A, there is little evidence that contagion exposures of developed markets depend on country fundamentals. In contrast, Panel B presents strong evidence for the wake-up hypothesis among developing countries. Across different measures of fundamentals, we find a one-standard-deviation increase in fundamental strength to decrease global market exposure during crisis times by in between 0.037 and 0.10 (value weighted crisis measure) and 0.077 and 0.13 (equally-weighted crisis measure). Bekaert et al. (2014) also find evidence in support of the wake-up call hypothesis. Our results show that the relation between contagion impact and fundamentals seems to concentrate on emerging markets.

In Table 10 we test our **hypothesis III** that large and liquid stocks should be hit harder by contagion, especially in countries whose equity markets are better integrated with global capital markets. Panel A shows estimation results for developed countries. While there is little evidence that global and local factor exposures during crisis times vary with firm size or liquidity, we do find returns unrelated to the factors to be positively related to both firm size and liquidity. We do not find robust evidence that this effect depends on foreign market participation. Our findings are consistent with those in Baele et al. (2019) and indicate a flight to large and liquid stocks during stress times, but inconsistent with our initial hypotheses that foreign investors would above all sell large and liquid stocks when stress hits the market. Panel B reports results for emerging markets. Consistent with our expectations, global and local crisis exposures are positively related to foreign equity market participation (but only statistically significant for the latter), and especially so for the more liquid firms. We find strong contagion unrelated to the factors, but this contagion intensity seems largely unrelated to both country and firm characteristics.

Table 11 tests our **hypothesis IV** that large and highly leverage firms should be more affected by contagion, especially in countries relying more heavily on foreign credit. Panel A shows that contagion unrelated to factors tends to be more intense for firms located in developed countries that rely more on foreign credit. Large firms, however, tend to be less exposed to this type of contagion, and even less so if they are located in countries that rely more on foreign credit. This suggests that large stocks are actually less affected by contagion in countries that borrow a lot from foreign banks. We do not find any robust relationship between excess factor exposures, firm characteristics, and foreign bank dependence. Turning to developing countries, Panel B reports that unconditionally, large firms are significantly less vulnerable to global and local contagion. Excess global factor exposures also decrease with firm leverage. However, the negative effect of firm size and leverage on excess global factor exposures is (partly) neutralized when they are interacted with foreign bank dependence. This is consistent with the idea that foreign banks mainly lend to large firms which are particularly affected when foreign lenders cut back on loans during a crisis. In unreported results, we also show that low Z-score firms are also significantly more affected by contagion if the country depends on cross-border credit. The findings are consistent with the argument that when foreign banks reduce lending, they first drop loans to risky firms with high leverage and a low Z-score.

4 Conclusion

In this paper we investigate the characteristics that protect or expose firms to market stressed periods. We develop a new methodology of crisis identification and build a predictive model for firm global and local equity market exposures. We focus on abnormal price movements for each firm by subtracting predicted factor exposures (in 'normal times') times the factor returns from weekly stock returns. We observe a substantial variation in contagion effects across firm and country characteristics in developing countries, but much less variation in developed ones. Second, stocks in developing countries with quality characteristics such as high ROE and low earnings volatility are related to significantly less global contagion or local contagion, consistent with a flight-to-quality hypothesis. Third, we find evidence of contagion caused by a wake-up call, as developing countries that have weaker domestic fundamentals are hit harder by global contagion. Moreover, higher liquidity leads to significantly higher exposure to both global and local contagion, especially in emerging markets with higher equity market openness. Also, larger and more higly levered stocks in countries highly dependent on foreign banks tend to be more vulnerable to global contagion. The results suggest that investor fire-sales and global credit contraction play an important role in the occurrence of contagion.

This version of the paper mainly serves to outline our overall empirical strategy and to present a first set of results. Progress is needed on all aspects of the paper. First efforts will be directed to finetuning further the crisis identification method. Currently, we have developed a data-light method to identify crises periods. To set some key parameters, which we do now in a rather adhoc way, it is our intention to fit our model to various crises indicators for the US, including some self-created text-based measure. We will then use these fine-tuned parameters to also estimate crises in other markets. Second, further hypotheses setting is necessary, both in the modeling of firm level factor exposures and in the excess contagion tests. This step will require a deeper reading of both the theoretical and empirical literature, and most likely, the collection of additional data.

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Table 1: Crisis Indicator

This table reports summary statistics for the crisis indicator developed in Section 2.1. Panel A reports for each developed country the average incidence and return impact of local, global, and developed-markets-only crises. Panel B reports corresponding statistics for developing markets.

Panel A: Developed Markets

	Local Crisis		Global Crisis				Developed Markets Crisis			
			75% VW		66% EW		75% VW		66% EW	
	Incidence	Impact	Incidence	Impact	Incidence	Impact	Incidence	Impact	Incidence	Impact
Australia	16.16	-0.68	8.49	-1.04	4.86	-2.08	10.94	-0.81	7.11	-1.41
Austria	19.07	-0.36	8.49	-1.27	4.86	-2.01	10.94	-0.87	7.11	-1.31
Belgium	16.36	-0.61	8.49	-1.21	4.86	-1.69	10.94	-0.86	7.11	-1.19
Canada	14.88	-0.69	8.49	-1	4.86	-1.58	10.94	-0.87	7.11	-1.14
Denmark	19.27	-0.48	8.49	-1.09	4.86	-1.6	10.94	-0.78	7.11	-1.17
Finland	15.21	-1.05	9.54	-0.98	5.24	-1.94	12.28	-1.11	8.04	-1.18
France	22.49	-0.43	8.49	-1.26	4.86	-1.94	10.94	-1.06	7.11	-1.45
Germany	18.81	-0.77	8.49	-1.37	4.86	-1.9	10.94	-1.09	7.11	-1.35
Hong Kong	17.02	-1.35	8.49	-1.24	4.86	-2.33	10.94	-1.02	7.11	-1.59
Ireland	16.82	-0.82	8.49	-1.24	4.86	-2.23	10.94	-0.84	7.11	-1.59
Israel	15.35	-1	10.92	-0.91	6.05	-1.3	14.17	-0.71	9.3	-0.9
Italy	17.38	-0.7	8.49	-1.31	4.86	-1.94	10.94	-1.1	7.11	-1.43
Japan	18.35	-0.88	8.49	-0.72	4.86	-1.15	10.94	-0.79	7.11	-0.69
Luxembourg	16.42	-0.56	10.52	-1.11	5.83	-0.9	13.65	-0.89	8.96	-0.8
Netherlands	18.30	-0.6	8.49	-1.33	4.86	-1.96	10.94	-1.09	7.11	-1.52
New Zealand	19.12	-0.66	9.47	-0.97	5.2	-1.46	12.19	-0.74	7.98	-0.95
Norway	16.46	-0.72	8.49	-1.16	4.86	-2.21	10.94	-0.9	7.11	-1.43
Portugal	19.78	-0.77	10.12	-1.32	5.56	-1.74	13.03	-1.1	8.53	-1.32
Singapore	15.39	-1.02	8.49	-1.47	4.86	-1.96	10.94	-1.1	7.11	-1.26
Spain	19.10	-0.76	10	-1.15	5.54	-1.91	12.89	-0.89	8.19	-1.34
Sweden	15.50	-0.89	8.61	-1.37	4.77	-2.15	11.09	-1.1	7.05	-1.46
Switzerland	13.29	-0.91	8.49	-0.91	4.86	-1.42	10.94	-0.75	7.11	-1.06
UK	16.72	-0.57	8.49	-1.1	4.86	-1.74	10.94	-0.92	7.11	-1.28
US	18.10	-0.6	8.49	-1.01	4.86	-1.41	10.94	-0.86	7.11	-0.98
Median	16.92	-0.71	8.49	-1.16	4.86	-1.91	10.94	-0.89	7.11	-1.30
Min	13.29	-1.35	8.49	-1.47	4.77	-2.33	10.94	-1.11	7.05	-1.59
Max	22.49	-0.36	10.92	-0.72	6.05	-0.90	14.17	-0.71	9.30	-0.69
Quartile 1	16.00	-0.88	8.49	-1.28	4.86	-1.97	10.94	-1.09	7.11	-1.43
Quartile 3	18.88	-0.60	8.83	-1.01	4.95	-1.55	11.37	-0.83	7.33	-1.12

Table 1 continued...

Panel B: Developing Markets

	Local Crisis		Global Crisis				Developed Markets Crisis			
			75% VW		66% EW		50% VW		66% EW	
	Incidence	Impact	Incidence	Impact	Incidence	Impact	Incidence	Impact	Incidence	Impact
Argentina	13.66	-1.98	11.17	-1.02	6.19	-1.49	12.08	-1.03	5.51	-1.27
Brazil	20.60	-1.37	11.59	-1.59	6.42	-1.58	12.22	-1.17	5.72	-2.01
Chile	16.84	-0.33	9.95	-0.7	5.46	-0.89	11.18	-0.53	4.81	-1.22
China	18.25	-0.38	11.16	-0.33	6.18	-1.09	12.07	-0.7	5.51	-1.86
Colombia	19.81	-0.56	10.59	-0.71	5.87	-0.85	11.44	-1.11	5.22	-1.07
Cyprus	20.78	-0.85	10.91	-1.95	6.04	-2.03	11.79	-1.33	5.38	-1.41
Czech	19.07	-0.6	11.29	-0.85	6.25	-1.25	12.2	-0.7	5.57	-1.14
Egypt	17.76	-1.01	12.76	-0.76	7.07	-1.13	13.45	-1.06	6.29	-1.36
Greece	17.59	-1.3	10.12	-1.55	5.56	-2.15	10.91	-0.82	4.89	-1.1
Hungary	17.91	-0.53	10.31	-1.64	5.71	-2.45	11.22	-1.31	5.09	-1.96
India	19.25	-0.51	10.12	-1.09	5.56	-1.51	10.91	-1.11	4.89	-1.77
Indonesia	19.81	-1.29	10.21	-1.8	5.6	-1.75	11.01	-1.33	4.94	-2.4
Lithuania	18.95	-0.91	13.59	-1.09	7.39	-1.83	12.11	-1.41	6.38	-2.03
Malaysia	15.07	-0.69	9.94	-0.98	5.46	-1.2	11.24	-0.93	4.81	-2.04
Mexico	18.97	-0.89	9.94	-1.12	5.46	-1.63	11.24	-1.08	4.81	-1.66
Pakistan	15.52	-0.81	10.73	-0.75	5.95	-1.25	11.6	-1.49	5.29	-1.55
Peru	21.03	-0.63	11.36	-0.65	6.29	-1.16	12.05	-0.78	5.6	-1.4
Philippines	14.10	-1.1	9.94	-1.46	5.46	-1.57	11.24	-0.61	4.81	-2.19
Poland	18.46	-0.94	11.43	-1.32	6.33	-2.2	12.05	-1.21	5.64	-1.54
Romania	20.09	-1.2	12.87	-2.05	7.13	-3.3	13.57	-2.23	6.35	-2.93
Russia	14.21	-0.86	13.47	-1.39	7.33	-2.87	12.83	-1.38	6.42	-3.36
Slovakia	19.13	-0.32	11.36	-0.42	10.16	-0.58	10.76	-0.57	6.73	-0.26
South Africa	13.71	-0.88	9.94	-1.03	5.46	-1.32	11.24	-0.65	4.81	-1.97
South Korea	14.17	-0.48	9.94	-1.34	5.46	-1.7	11.24	-0.89	4.81	-1.93
Sri Lanka	17.48	-0.06	9.94	-0.58	5.46	-0.6	11.24	-0.22	4.81	-1.03
Taiwan	15.14	-0.85	9.94	-1.59	5.46	-1.51	11.24	-0.68	4.81	-1.76
Thailand	14.04	-0.73	9.94	-1.46	5.46	-1.41	11.24	-0.62	4.81	-2.45
Turkey	21.90	-0.95	9.94	-1.3	5.46	-1.9	11.24	-0.45	4.81	-2.2
Median	18.08	-0.85	10.45	-1.11	5.79	-1.51	11.24	-0.98	5.16	-1.77
Min	13.66	-1.98	9.94	-2.05	5.46	-3.30	10.76	-2.23	4.81	-3.36
Max	21.9	-0.06	13.59	-0.33	10.16	-0.58	13.57	-0.22	6.73	-0.26
Quartile 1	15.12	-0.97	9.94	-1.48	5.46	-1.85	11.24	-1.24	4.81	-2.03
Quartile 3	19.39	-0.55	11.36	-0.76	6.30	-1.19	12.07	-0.67	5.61	-1.34

Table 2: Stocks and Firm Characteristics Availability by Country

This table reports the availability of stock and firm characteristics for each country over the period July 1981 to December 2018. The sample includes only non-financial common stocks listed on its country's major exchange(s) and that are the main issue of their company. To address the potential biases from illiquid stocks, we drop the stocks that have a proportion of more than 75% zero daily returns during the previous July-June period. Stocks are also required to have at least 126 trading days during a July-June period. The total and average numbers of stocks are reported for each country, as well as the year of the first entry. The remaining columns show the time-series average of percentage of firms that have observations for the Book-to-Market (BM) ratio, Total Leverage, the Z-score, Earnings Volatility, Return on Equity (ROE), and Gross Profits. Leverage and gross profits are all scaled by total asset.

Panel A: Developed Markets

				Time-Series Average of % of Firms that have Data on:					
Country	Starting Year	Total # of Firms	Average % of Firms	Book-to-Market Ratio	Total Leverage	Altman Z-score	Earnings Volatility	Return on Equity	Gross Profit
Australia	1981	2448	628	80	81	76	85	75	77
Austria	1981	116	39	87	91	78	88	86	85
Belgium	1981	158	61	89	91	58	87	86	83
Canada	1981	1723	617	71	74	66	74	68	71
Denmark	1981	196	71	91	93	74	90	89	88
Finland	1987	188	82	94	97	93	92	94	92
France	1981	1299	408	91	95	84	88	89	87
Germany	1981	888	334	86	89	81	82	84	80
Hong Kong	1981	1358	428	85	88	81	85	82	87
Ireland	1981	71	23	88	92	82	87	87	89
Israel	1986	367	173	59	60	55	60	53	59
Italy	1981	421	141	93	95	87	88	90	91
Japan	1981	3481	1929	90	92	83	94	88	91
Luxembourg	1992	15	7	83	87	62	85	84	70
Netherlands	1981	223	101	83	85	37	83	81	81
New Zealand	1986	176	56	82	85	78	88	79	79
Norway	1981	368	85	91	94	64	87	88	86
Portugal	1988	86	39	89	91	89	87	84	89
Singapore	1981	539	191	86	89	74	89	83	87
Spain	1986	205	83	95	96	92	90	92	94
Sweden	1982	772	195	89	92	90	87	88	87
Switzerland	1981	249	111	90	93	83	89	89	90
UK	1981	3199	833	86	88	79	86	79	84
US	1981	7442	2667	90	92	74	87	85	89
Total # Firms		25,988							

Table 2 continued...

Panel B: Developing Markets

				Time-Series Average of % of Firms that have Data on:					
Country	Starting Year	Total # of Firms	Average # of Firms	Book-to-Market Ratio	Total Leverage	Altman Z-score	Earnings Volatility	Return on Equity	Gross Profit
Argentina	1988	87	36	87	89	83	85	84	87
Bangladesh	1992	75	31	51	54	51	58	46	54
Brazil	1994	163	62	94	97	84	87	89	96
Chile	1990	132	53	83	85	82	84	80	84
China	1991	3189	1166	83	93	89	83	89	93
Colombia	1992	31	12	87	91	86	87	87	91
Cyprus	1994	71	20	34	42	38	51	34	42
Czech	1994	79	22	58	59	58	72	47	58
Egypt	1996	133	75	77	77	65	78	71	78
Greece	1988	335	161	88	89	82	90	83	81
Hungary	1991	53	22	87	87	82	84	81	88
Iceland	2001	18	7	79	80	79	79	76	80
India	1983	1294	566	56	57	26	64	47	58
Indonesia	1990	446	160	90	92	80	87	84	92
Lithuania	1998	38	17	66	69	66	72	60	69
Malaysia	1981	877	396	84	85	75	86	79	84
Mexico	1988	121	44	92	95	87	92	89	94
Pakistan	1991	243	124	76	77	57	80	68	76
Peru	1992	64	20	87	89	84	89	84	87
Philippines	1988	166	65	89	89	82	85	84	89
Poland	1992	562	205	85	87	87	81	81	87
Romania	1997	95	46	67	66	64	72	58	67
Russia	1996	244	82	89	96	92	84	88	96
Slovakia	2000	5	2	100	100	94	92	97	100
South Africa	1981	553	141	82	85	77	86	78	73
South Korea	1981	2262	894	75	77	71	75	71	75
Sri Lanka	1987	175	81	69	71	62	75	63	69
Taiwan	1988	945	506	86	87	80	84	83	87
Thailand	1987	647	270	84	86	46	84	82	87
Turkey	1988	341	166	82	83	80	82	76	83
Total # Firms		13,444							

Table 3: Firm-Level Data Summary Statistics

This table reports summary statistics of firm-level data. For each country, time series mean of cross-sectional value-weighted and equally-weighted excess return denominated in US dollar are reported. The column TOTMK reports the time-series mean of Datastream stock market index for each country. Weekly risk-free rate is based on one-month US Treasury bill yield from CRSP. We also report the time series mean of cross-sectional median of stock return and firm characteristics including dividend yield, market capitalizatoin, book-to-market, illiquidity as the proportion of zero returns, total leverage, tangibility, Z-score, earnings volatility, return on equity, gross profit. Leverage and gross profit are all scaled by total asset. Size is the market capitalizaiton in millions at the end of June. Except for Size, BM, and Earnings VOL, other variables are all in percentage.

Panel A: Developed Markets

	Time-Series Average of:				Time-Series average of median:							
	Return on Datastream's Total Market Index	Value-Weighted Return	Eq Weighted Return	Median Return	Market Value (mn $)	Book-to-Market ratio	% Zero returns	Total Leverage	Altman Z-score	Earnings Volatility	Return on Equity	Gross Profit
Australia	0.13	0.12	0.25	-0.20	49.89	0.68	42.65	11.26	6.48	0.69	1.85	5.17
Austria	0.16	0.09	0.18	0.06	358.41	0.62	25.46	20.65	5.73	0.60	9.26	15.05
Belgium	0.17	0.19	0.23	0.07	161.37	0.82	24.46	22.29	5.49	0.70	10.14	8.91
Canada	0.11	0.07	0.38	-0.16	95.42	0.63	25.43	18.80	6.02	0.87	5.62	10.60
Denmark	0.19	0.19	0.20	0.03	130.45	0.73	30.82	22.11	6.48	0.70	9.96	19.73
Finland	0.17	0.16	0.16	0.01	191.50	0.73	25.36	28.07	6.17	0.90	10.22	25.59
France	0.19	0.19	0.24	-0.05	129.34	0.67	18.59	18.93	5.82	0.63	10.40	9.93
Germany	0.14	0.13	0.19	-0.10	138.45	0.55	18.03	13.08	6.13	0.71	8.18	25.35
Hong Kong	0.17	0.16	0.23	-0.29	94.05	0.78	30.20	14.80	7.01	0.72	12.43	11.02
Ireland	0.16	0.12	0.20	0.19	263.80	0.69	44.83	23.29	6.11	0.65	10.38	18.42
Israel	0.11	0.13	0.37	-0.06	36.95	0.68	28.93	25.22	6.01	0.89	8.28	20.01
Italy	0.10	0.14	0.10	-0.16	171.12	0.77	14.25	23.66	5.53	0.76	6.80	19.34
Japan	0.07	0.10	0.18	-0.13	254.76	0.76	18.15	18.95	6.13	0.62	5.91	21.68
Luxembourg	0.13	0.15	0.20	0.31	396.52	0.87	31.89	9.82	6.09	0.68	14.81	22.57
Netherlands	0.17	0.19	0.22	0.00	311.30	0.77	15.42	19.43	5.67	0.61	13.38	25.41
New Zealand	0.15	0.16	0.18	0.09	129.50	0.63	37.67	25.39	6.52	0.47	11.56	13.81
Norway	0.21	0.19	0.20	-0.03	116.09	0.69	28.08	29.63	5.44	1.05	8.63	13.59
Portugal	0.06	0.08	0.12	-0.08	179.16	0.83	25.98	36.07	4.58	0.76	7.88	4.94
Singapore	0.09	0.09	0.18	-0.07	97.71	0.81	37.52	13.59	6.98	0.65	9.31	10.92
Spain	0.13	0.14	0.11	-0.08	495.30	0.70	14.75	26.03	5.14	0.57	9.56	14.19
Sweden	0.22	0.21	0.30	-0.06	77.44	0.57	27.57	17.25	6.12	0.73	9.68	12.51
Switzerland	0.17	0.18	0.16	0.04	296.89	0.70	26.46	19.31	6.99	0.49	9.23	22.20
UK	0.14	0.15	0.13	-0.17	119.44	0.56	41.93	13.15	6.56	0.60	11.42	26.07
US	0.15	0.16	0.30	-0.01	354.37	0.51	15.43	19.63	6.82	0.62	10.17	32.88

Table 3 continued...

Panel B: Developing Markets

	Time-Series Average of:				Time-Series average of median:							
	Return on Datastream's Total Market Index	Value-Weighted Return	Eq Weighted Return	Median Return	Market Value (mn $)	Book-to-Market ratio	% Zero returns	Total Leverage	Altman Z-score	Earnings Volatility	Return on Equity	Gross Profit
Argentina	0.11	0.15	0.19	-0.14	132.78	0.91	33.00	22.09	5.70	1.13	8.58	17.40
Bangladesh		0.26	0.43	0.04	52.95	0.31	25.32	23.47	7.28	0.30	18.46	15.74
Brazil	0.22	0.34	0.37	-0.05	705.54	0.89	22.15	26.46	5.77	0.78	8.72	16.57
Chile	0.21	0.19	0.23	0.07	503.36	0.67	34.71	26.12	6.53	0.52	11.93	14.37
China	0.23	0.20	0.31	-0.16	421.96	0.39	13.32	22.25	6.34	0.57	8.53	11.05
Colombia	0.12	0.22	0.19	0.24	1122.94	1.04	37.93	12.70	7.02	0.42	6.74	10.95
Cyprus	0.06	0.09	0.24	0.34	56.96	2.11	57.10	26.68	6.12	0.82	5.57	14.63
Czech	0.16	0.16	0.16	0.29	705.21	1.13	22.25	16.88	6.20	0.57	10.66	12.74
Egypt	0.14	0.08	0.17	-0.25	69.83	0.72	24.59	16.04	6.44	0.43	16.19	14.28
Greece	0.05	0.11	0.24	-0.22	44.63	0.97	29.41	26.01	6.06	0.73	7.50	17.17
Hungary	0.20	0.22	0.25	0.28	57.41	0.88	26.66	14.42	6.80	0.70	8.77	18.62
Iceland		0.22	0.23	0.54	382.84	0.57	29.67	37.22	5.52	0.94	9.74	26.88
India	0.21	0.06	0.59	-0.36	5.49	0.98	28.61	31.16	5.12	0.76	9.82	12.02
Indonesia	0.11	0.14	0.30	-0.30	92.40	0.76	45.08	31.32	6.10	0.89	10.11	15.46
Lithuania	0.15	0.37	0.34	0.14	66.44	1.06	54.72	21.99	6.21	0.96	7.20	17.62
Malaysia	0.16	0.14	0.23	-0.15	62.61	0.86	32.73	16.65	6.79	0.66	8.50	10.13
Mexico	0.24	0.23	0.21	0.04	889.23	0.81	20.02	22.88	7.08	0.59	10.84	20.34
Pakistan	0.14	0.19	0.33	-0.18	32.37	0.77	29.97	30.76	5.15	0.56	16.67	14.58
Peru	0.19	0.17	0.26	0.15	308.38	0.77	48.70	19.81	6.52	0.68	13.48	19.80
Philippines	0.17	0.18	0.35	-0.14	89.16	0.85	41.70	21.43	7.19	0.66	13.59	12.98
Poland	0.09	0.05	0.13	-0.30	31.81	0.76	23.07	11.79	6.81	0.96	9.19	22.52
Romania	0.12	0.14	0.43	-0.22	14.52	1.56	41.58	8.33	8.16	0.86	4.28	16.74
Russia	0.33	0.40	0.49	-0.03	643.12	1.55	18.70	18.83	6.89	0.86	10.48	21.59
Slovakia	0.17	0.65	0.71	1.81	537.19	1.59	57.82	12.02	6.78	2.43	7.52	13.92
South Africa	0.17	0.14	0.26	-0.01	253.35	0.60	35.46	11.16	7.25	0.48	18.50	21.53
South Korea	0.16	0.17	0.29	-0.36	52.73	1.09	14.97	32.09	5.59	0.93	5.97	13.95
Sri Lanka	0.14	0.17	0.25	0.04	11.07	0.91	51.44	22.92	6.46	0.60	11.66	15.65
Taiwan	0.12	0.12	0.17	-0.24	212.15	0.67	15.09	21.21	6.86	0.59	8.90	12.99
Thailand	0.22	0.20	0.26	-0.17	51.00	0.76	32.86	28.30	5.59	0.67	11.66	20.06
Turkey	0.29	0.35	0.45	-0.37	62.69	0.60	29.62	20.76	6.58	0.93	13.80	23.46

Table 4: Country variable coverage

Trade is the sum of exports and imports of a country vis-a-vis the world. De jure integration measure is from Fernández, Klein, Rebucci, Schindler and Uribe (2016). Foreign asset and liability is from Philip R. Lane and Gian Maria Milesi-Ferretti (2017). Stock market Capitalization is from Financial Development and Structure Dataset. Foreign bank ownership is from CvH Bank Ownership Database. Cross-border borrowing is from BIS-Locational banking statistics, where claims are grouped from a residence perspective and adjusted for breaks in series and exchange rate movement. Foreign borrowing is from BIS-Consolidated banking statistics, where claims are grouped from a nationality perspective. Short-term foreign borrowing are those with maturity lower than 1 year. Local-in-local borrowing are extended by foreign bank subsidiaries denominated in local currency. All absolute values are scaled by GDP.

Panel A: Developed Markets

	Trade	De jure openness:	De facto openness:	Cross-border borrowing		Foreign borrowing
		Equity market	Equity Asset+Liability	by banks	by non-banks	(based on nationality of banks)
Australia	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Austria	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Belgium	1997-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Canada	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Denmark	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Finland	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
France	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Germany	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Hong Kong	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Ireland	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Israel	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Italy	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Japan	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Luxembourg	1997-2018		1990-2015	1983-2018	1983-2018	1999-2018
Netherlands	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
New Zealand	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Norway	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Portugal	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Singapore	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Spain	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Sweden	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
Switzerland	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
UK	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018
US	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1999-2018

Table 4 continued...

Panel B: Developing Markets

	Trade/GDP	De jure openness: Equity market	De facto openness: Equity Asset+Liability	Cross-border borrowing by banks	Cross-border borrowing by non-banks	Foreign borrowing (based on nationality of banks)
Argentina	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Bangladesh	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Brazil	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Chile	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
China	1980-2018	1980-2016	1981-2015	1980-2018	1980-2018	1983-2018
Colombia	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Cyprus	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1984-2018
Czech	1995-2018	1980-2016	1993-2015	1995-2018	1995-2018	1995-2018
Egypt	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Greece	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Hungary	1980-2018	1980-2016	1982-2015	1980-2018	1980-2018	1983-2018
Iceland	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1985-2018
India	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Indonesia	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Lithuania	1995-2018		1992-2015	1995-2018	1995-2018	2000-2018
Malaysia	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Mexico	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Pakistan	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Peru	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Philippines	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Poland	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Romania	1980-2018	1980-2016	1990-2015	1980-2018	1980-2018	1983-2018
Russia	1992-2018	1980-2016	1993-2015	1993-2018	1993-2018	1993-2018
Slovakia	1993-2018		1993-2015	1993-2018	1993-2018	1993-2018
South Africa	1998-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
South Korea	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Sri Lanka	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Taiwan	1980-2016		1980-2015	1980-2018	1980-2018	1983-2018
Thailand	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018
Turkey	1980-2018	1980-2016	1980-2015	1980-2018	1980-2018	1983-2018

Table 5: Country beta prediction

This table presents estimation results for the country-level global beta prediction model developed in Section 2.2.1. Panel A and B report results for developed and developing countries, respectively, using both the equally and value-weighted global crisis indicator.

Panel A: Developed countries

	VW 75%		EW 66%	
	(1)	(2)	(3)	(4)
Beta: Last year	0.13***	0.13***	0.14***	0.12***
	(3.01)	(2.89)	(3.10)	(2.84)
Beta: 5 year mean	0.51***	0.49***	0.51***	0.47***
	(9.56)	(8.66)	(9.35)	(8.32)
Crisis intensity: Current	0.14**	0.14**	0.20***	0.23***
	(2.39)	(2.20)	(2.68)	(2.89)
Crisis intensity: Last year	-0.12*	-0.084	-0.054	-0.0033
	(-1.80)	(-1.21)	(-0.66)	(-0.04)
Crisis intensity: 5 year mean	0.46***	0.40***	0.29*	0.28*
	(4.05)	(3.31)	(1.92)	(1.83)
Schindler		0.047		0.062
		(0.72)		(0.94)
Prtfolio Equity		0.015		0.022**
		(1.46)		(2.34)
Trade		-0.031*		-0.037**
		(-1.88)		(-2.28)
OECD		0.015		0.025**
		(1.35)		(2.23)
Adj. R-Square	0.33	0.34	0.33	0.33
N	815	815	815	815

Table 5 continued...

Panel B: Developing countries

	VW 75%		EW 66%	
	(1)	(2)	(3)	(4)
Beta: Last year	0.33***	0.28***	0.31***	0.23***
	(7.37)	(6.04)	(6.97)	(4.87)
Beta: 5 year mean	0.28***	0.32***	0.30***	0.36***
	(5.31)	(5.58)	(5.52)	(6.27)
Crisis intensity: Current	-0.058	-0.12	0.18	0.28**
	(-0.60)	(-1.16)	(1.54)	(2.11)
Crisis intensity: Last year	-0.18*	-0.075	-0.061	0.13
	(-1.74)	(-0.66)	(-0.48)	(0.95)
Crisis intensity: 5 year mean	0.24	-0.0064	-0.23	-0.50**
	(1.32)	(-0.03)	(-0.99)	(-2.09)
Schindler		0.026		0.013
		(0.55)		(0.29)
Prtfolio Equity		0.082***		0.081***
		(3.97)		(3.90)
Trade		-0.053		-0.055*
		(-1.59)		(-1.65)
OECD		0.031		0.074***
		(1.56)		(3.66)
Adj. R-Square	0.32	0.37	0.32	0.38
N	748	678	748	678

Table 6: Firm global beta prediction

This table reports estimation results for the firm-level global (Panel A) and local (Panel B) beta prediction model outlined in Section 2.2.2.

Panel A: Global beta prediction

	Developed countries		Developing countries	
	VW 75%	EW 66%	VW 75%	EW 66%
Beta last year	0.14***	0.15***	0.0071	0.0067
	(9.07)	(8.67)	(0.16)	(0.15)
Beta 5 year average	0.25***	0.26***	0.34***	0.34***
	(12.64)	(11.84)	(8.65)	(9.13)
Country beta last year	0.13**	0.14**	0.14*	0.12*
	(2.11)	(2.22)	(1.93)	(1.69)
Country beta 5 year average	0.21***	0.19***	-0.10*	-0.095
	(3.43)	(2.97)	(-1.70)	(-1.52)
Crisis intensity	-0.25***	-0.17***	-0.12	-0.15
	(-5.86)	(-3.72)	(-1.29)	(-1.53)
Crisis intensity last year	-0.15***	-0.098*	0.078	0.17*
	(-4.08)	(-1.75)	(0.97)	(1.95)
Crisis intensity 5 year average	0.62***	0.32**	0.14	-0.075
	(5.07)	(2.44)	(0.66)	(-0.38)
Schindler	0.023	0.011	0.18***	0.18***
	(0.34)	(0.15)	(4.03)	(3.68)
Portfolio equity	0.00015	0.00022	0.049***	0.051***
	(0.01)	(0.01)	(2.68)	(2.81)
Trade	-0.021*	-0.017	0.023	0.020
	(-1.76)	(-1.34)	(1.39)	(1.15)
Size	0.11***	0.096***	0.029*	0.028*
	(14.95)	(13.85)	(1.84)	(1.78)
Liquidity	0.073***	0.075***	0.046***	0.047***
	(8.73)	(8.63)	(4.86)	(5.00)
IVOL	0.16***	0.15***	0.080***	0.079***
	(24.70)	(21.06)	(5.31)	(5.40)
B/M	-0.0028	-0.0015	0.019*	0.018*
	(-0.53)	(-0.28)	(1.92)	(1.81)
Leverage	0.0040	0.00097	0.0071	0.0067
	(1.01)	(0.22)	(1.46)	(1.31)
Z-score	0.0086**	0.0064*	-0.0059	-0.0057
	(2.51)	(1.82)	(-1.52)	(-1.39)
Gross profit	-0.022***	-0.023***	0.016**	0.016*
	(-6.42)	(-6.20)	(1.98)	(1.88)
Adj. R-Square	0.31	0.30	0.18	0.17
N	246,021	246,021	97,673	97,673

Table 6 continued...

Panel B: Local Beta Prediction

	Developed countries	Developing countries
Beta last year	0.087***	0.095
	(6.97)	(1.43)
Beta 5 year average	0.28***	0.48***
	(12.48)	(7.19)
Local crisis intensity	-0.10*	-0.019
	(-1.67)	(-0.19)
Local crisis intensity last year	-0.11*	-0.0025
	(-1.74)	(-0.04)
Local crisis intensity 5 year average	0.23***	-0.17
	(3.10)	(-1.10)
Size	0.11***	0.024
	(10.73)	(0.87)
Liquidity	0.061***	0.021
	(4.62)	(1.26)
IVOL	0.13***	0.10***
	(12.20)	(3.67)
B/M	0.0080	0.028**
	(1.35)	(2.55)
Leverage	-0.00081	0.0031
	(-0.14)	(0.70)
Z-score	0.0059	0.0029
	(1.47)	(0.83)
Gross profit	-0.013**	0.019**
	(-2.09)	(2.41)
Adj. R-Square	0.13	0.19
N	246,021	97,624

Table 7: Abnormal Returns

This table reports summary statistics for abnormal returns and their correlation with global and local factors. Panel A reports for each developed country the cross-sectional mean of time series average of abnormal returns, as well as the average correlation between abnormal returns and factors. Panel B reports corresponding statistics for developing markets.

Panel A: Developed Markets

	Global Crisis 75% VW			Global Crisis 66% EW		
	Abnormal return	Correlation with world factor	Correlation with local factor	Abnormal return	Correlation with world factor	Correlation with local factor
Australia	-0.22	-0.01	-0.01	-0.32	-0.01	-0.01
Austria	-0.06	-0.08	-0.09	0.19	-0.09	-0.10
Belgium	-0.18	-0.06	-0.15	-0.12	-0.07	-0.16
Canada	0.23	-0.01	-0.03	0.21	0.02	-0.00
Denmark	-0.24	-0.05	-0.06	-0.32	-0.04	-0.04
Finland	-0.10	-0.18	-0.29	0.11	-0.12	-0.17
France	-0.15	-0.12	-0.13	-0.15	-0.10	-0.10
Germany	0.05	-0.09	-0.13	0.04	-0.07	-0.13
Hong Kong	-0.18	-0.05	-0.05	-0.23	-0.06	-0.06
Ireland	-0.18	-0.12	-0.17	-0.15	-0.14	-0.21
Israel	-0.06	-0.03	-0.05	-0.03	-0.03	-0.05
Italy	0.02	-0.10	-0.08	-0.04	-0.11	-0.09
Japan	0.16	-0.06	-0.05	0.22	-0.03	0.01
Netherlands	0.01	-0.11	-0.12	0.09	-0.10	-0.11
New Zealand	-0.28	0.14	0.15	-0.51	0.15	0.16
Norway	-0.35	-0.08	-0.11	-0.46	-0.08	-0.12
Portugal	0.02	-0.06	-0.05	0.08	-0.07	-0.08
Singapore	-0.25	0.01	0.02	-0.21	0.01	0.02
Spain	-0.07	-0.13	-0.17	-0.09	-0.11	-0.16
Sweden	-0.06	-0.09	-0.13	-0.12	-0.09	-0.11
Switzerland	-0.39	-0.06	-0.08	-0.28	-0.01	-0.01
UK	-0.36	-0.07	-0.08	-0.43	-0.07	-0.08
US	0.22	-0.06	-0.07	0.13	-0.05	-0.05
Median	-0.10	-0.06	-0.08	-0.11	-0.07	-0.08
Min	-0.39	-0.18	-0.29	-0.51	-0.14	-0.20
Max	0.23	0.14	0.15	0.22	0.15	0.16
Quartile 1	-0.24	-0.10	-0.13	-0.28	-0.10	-0.12
Quartile 3	0.02	-0.05	-0.05	0.09	-0.03	-0.01

Table 7 continued...

Panel B: Developing Markets

	Global Crisis 75% VW			Global Crisis 66% EW		
	Abnormal return	Correlation with world factor	Correlation with local factor	Abnormal return	Correlation with world factor	Correlation with local factor
Argentina	-0.30	0.09	-0.05	-0.39	0.16	-0.02
Brazil	-0.38	0.08	0.08	-0.21	0.06	0.06
Chile	-0.04	-0.09	-0.02	0.07	-0.13	-0.05
China	0.30	-0.26	-0.29	0.06	-0.31	-0.33
Colombia	0.19	0.06	0.15	-0.28	0.12	0.14
Cyprus	0.60	-0.15	-0.29	0.77	-0.14	-0.29
Czech	0.02	-0.20	-0.19	0.11	-0.16	-0.19
Egypt	0.61	-0.16	-0.06	0.73	-0.17	-0.07
Greece	-0.01	-0.06	-0.05	0.42	-0.06	-0.08
Hungary	-0.25	-0.10	-0.05	-0.47	-0.10	-0.03
India	-0.56	0.05	-0.00	-0.47	0.08	0.02
Indonesia	-0.06	0.04	0.00	-0.13	0.02	-0.04
Malaysia	0.14	-0.08	-0.01	0.19	-0.10	-0.05
Mexico	-0.49	0.03	0.03	-0.55	0.07	0.07
Pakistan	-0.13	-0.04	-0.07	-0.11	-0.03	-0.10
Peru	-0.04	-0.04	0.05	-0.02	-0.06	0.06
Philippines	-0.28	0.05	0.06	-0.45	0.05	0.07
Poland	-0.51	0.07	0.00	-0.60	0.03	-0.03
Romania	0.04	-0.05	-0.06	0.08	-0.06	-0.07
Russia	-0.50	-0.04	-0.06	-0.53	-0.11	-0.13
South Africa	-0.25	-0.05	-0.06	-0.23	-0.04	-0.06
South Korea	0.20	-0.01	0.08	0.22	-0.03	0.11
Sri Lanka	0.48	-0.04	0.14	0.48	-0.05	0.14
Thailand	-0.02	-0.02	-0.03	0.08	-0.04	-0.06
Turkey	-0.11	0.17	0.15	-0.40	0.18	0.15
Median	-0.04	-0.04	-0.02	-0.11	-0.04	-0.04
Min	-0.56	-0.26	-0.29	-0.60	-0.30	-0.33
Max	0.61	0.16	0.08	0.77	0.18	0.15
Quartile 1	-0.28	-0.08	-0.06	-0.40	-0.10	-0.07
Quartile 3	0.14	0.05	0.05	0.11	0.05	0.06

Table 8: Quality stocks and contagion

This table reports the estimates for the contagion coefficient for Hypothesis I. *,**, and *** indicates statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by week.

Panel A: Developed countries

	Global crisis VW 75%					Global crisis EW 66%						
	(1)	(2) ROE	(3) Z-score	(4) Leverage	(5) EPS Vol	(6) Full	(7)	(8) ROE	(9) Z-score	(10) Leverage	(11) EPS Vol	(12) Full
Global × Crisis	-0.057	-0.059	-0.057	-0.057	-0.056	-0.059	-0.027	-0.027	-0.028	-0.027	-0.029	-0.029
	(-1.55)	(-1.61)	(-1.55)	(-1.57)	(-1.55)	(-1.64)	(-0.60)	(-0.59)	(-0.61)	(-0.60)	(-0.64)	(-0.64)
Local × Crisis	-0.079***	-0.076**	-0.080***	-0.078***	-0.080***	-0.076**	-0.020	-0.018	-0.021	-0.019	-0.021	-0.019
	(-2.67)	(-2.56)	(-2.69)	(-2.63)	(-2.72)	(-2.57)	(-0.55)	(-0.51)	(-0.57)	(-0.52)	(-0.60)	(-0.53)
Crisis	-0.18*	-0.18*	-0.18*	-0.18*	-0.19*	-0.19*	-0.19	-0.18	-0.19	-0.19	-0.20	-0.20
	(-1.73)	(-1.70)	(-1.72)	(-1.74)	(-1.90)	(-1.90)	(-1.28)	(-1.25)	(-1.28)	(-1.31)	(-1.37)	(-1.38)
Global × Crisis × ROE		0.016				0.020		0.0099				0.013
		(1.20)				(1.51)		(0.69)				(0.87)
Local × Crisis × ROE		0.0039				0.0036		0.0043				0.0049
		(0.29)				(0.24)		(0.28)				(0.29)
Crisis × ROE		0.058				0.065		0.053				0.067
		(1.36)				(1.51)		(1.04)				(1.28)
Global × Crisis × Z-score			-0.0029			-0.0091			0.0035			-0.0011
			(-0.40)			(-0.98)			(0.48)			(-0.11)
Local × Crisis × Z-score			0.013			0.00077			0.0049			0.0011
			(1.07)			(0.06)			(0.35)			(0.07)
Crisis × Z-score			0.00061			0.0027			0.019			0.013
			(0.03)			(0.10)			(0.71)			(0.38)
Global × Crisis × Leverage				0.0072		0.0094				0.014		0.019*
				(0.66)		(0.88)				(1.29)		(1.87)
Local × Crisis × Leverage				-0.016		-0.015				-0.0084		-0.0082
				(-1.03)		(-1.02)				(-0.44)		(-0.49)
Crisis × Leverage				0.028		0.033				-0.015		-0.0089
				(0.76)		(0.94)				(-0.38)		(-0.26)
Global × Crisis × EPS vol					0.0016	0.0023					0.0031	0.0030
					(0.39)	(0.55)					(0.66)	(0.64)
Local × Crisis × EPS vol					-0.0066	-0.0039					-0.0016	0.0014
					(-1.10)	(-0.70)					(-0.19)	(0.17)
Crisis × EPS vol					-0.012	-0.014					-0.021	-0.020
					(-1.02)	(-1.10)					(-1.39)	(-1.28)
Adj. R-Square	0.00018	0.00022	0.00018	0.00018	0.00019	0.00025	0.000046	0.000081	0.000053	0.000055	0.000057	0.00012
N	12525780	11921124	12525780	12525780	11601454	11045012	12525780	11921124	12525780	12525780	11601454	11045012

Table 8 continued...

Panel B: Developing Markets

	Global crisis VW 75%					Global crisis EW 66%						
	(1)	(2) ROE	(3) Z-score	(4) Leverage	(5) EPS Vol	(6) Full	(7)	(8) ROE	(9) Z-score	(10) Leverage	(11) EPS Vol	(12) Full
Global × Crisis	-0.10*	-0.11*	-0.10*	-0.10*	-0.099	-0.10	-0.16**	-0.16**	-0.16**	-0.16**	-0.16**	-0.16**
	(-1.67)	(-1.71)	(-1.66)	(-1.67)	(-1.58)	(-1.61)	(-2.27)	(-2.31)	(-2.26)	(-2.27)	(-2.19)	(-2.22)
Local × Crisis	0.045	0.043	0.046	0.044	0.041	0.041	0.054	0.053	0.055	0.053	0.050	0.050
	(0.84)	(0.79)	(0.85)	(0.83)	(0.76)	(0.73)	(0.85)	(0.82)	(0.86)	(0.84)	(0.79)	(0.77)
Crisis	-0.24	-0.24	-0.23	-0.24	-0.29	-0.29	-0.39	-0.39	-0.38	-0.38	-0.44*	-0.44*
	(-1.19)	(-1.16)	(-1.18)	(-1.19)	(-1.46)	(-1.42)	(-1.53)	(-1.51)	(-1.52)	(-1.52)	(-1.73)	(-1.70)
Global × Crisis × ROE		-0.0011				-0.012		0.0029				-0.010
		(-0.08)				(-0.77)		(0.17)				(-0.56)
Local × Crisis × ROE		-0.036**				-0.040*		-0.047**				-0.054**
		(-2.10)				(-1.91)		(-2.40)				(-2.25)
Crisis × ROE		0.015				0.0054		0.0025				-0.014
		(0.31)				(0.09)		(0.04)				(-0.19)
Global × Crisis × Z-score			0.028**			0.019			0.038**			0.020
			(2.00)			(1.07)			(2.23)			(1.01)
Local × Crisis × Z-score			0.011			0.016			0.015			0.021
			(0.67)			(0.70)			(0.93)			(0.91)
Crisis × Z-score			0.068			0.077			0.096			0.075
			(1.08)			(0.93)			(1.14)			(0.80)
Global × Crisis × Leverage				-0.031**		-0.028***				-0.035**		-0.032***
				(-2.56)		(-2.77)				(-2.53)		(-2.72)
Local × Crisis × Leverage				-0.0081		-0.011				-0.015		-0.017
				(-0.47)		(-0.61)				(-0.86)		(-0.96)
Crisis × Leverage				-0.043		-0.0074				-0.070		-0.032
				(-0.84)		(-0.19)				(-1.06)		(-0.62)
Global × Crisis × EPS vol					0.014**	0.018***					0.013*	0.018***
					(2.20)	(2.92)					(1.86)	(2.60)
Local × Crisis × EPS vol					0.0064	0.0056					0.0084	0.0085
					(0.81)	(0.61)					(0.89)	(0.84)
Crisis × EPS vol					-0.0081	-0.0058					0.00070	0.011
					(-0.36)	(-0.27)					(0.02)	(0.38)
Adj. R-Square	0.00036	0.00040	0.00038	0.00039	0.00040	0.00050	0.00047	0.00054	0.00050	0.00050	0.00052	0.00064
N	4888557	4678334	4888557	4888557	4308447	4112901	4888557	4678334	4888557	4888557	4308447	4112901

Table 9: Wake-up call and contagion

This table reports the estimates for the contagion coefficient for Hypothesis II. *,**, and *** indicates statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by week.

Panel A: Developed countries,

	Global crisis VW 75%					Global crisis EW 66%				
	(1) Current Account	(2) Credit Rating	(3) FX Reserve	(4) Gov Budget	(5) Unemployment	(6) Current Account	(7) Credit Rating	(8) FX Reserve	(9) Gov Budget	(10) Unemployment
Global	-0.026*	-0.026*	-0.025*	-0.010	-0.027*	-0.016	-0.016	-0.015	0.00052	-0.016
	(-1.74)	(-1.77)	(-1.73)	(-0.67)	(-1.84)	(-1.13)	(-1.15)	(-1.09)	(0.04)	(-1.20)
Local	0.0029	0.00048	-0.0031	0.012	-0.0044	-0.011	-0.014	-0.017	-0.0013	-0.018
	(0.20)	(0.03)	(-0.23)	(0.77)	(-0.33)	(-0.79)	(-0.96)	(-1.31)	(-0.09)	(-1.43)
Global × Country fundamentals	-0.0022	-0.013	0.024**	0.015	-0.021**	-0.0046	-0.014*	0.024**	0.010	-0.017**
	(-0.33)	(-1.50)	(1.99)	(1.31)	(-2.52)	(-0.72)	(-1.68)	(2.02)	(0.99)	(-2.27)
Local × Country fundamentals	-0.00078	-0.0097	0.042	0.00067	-0.052***	-0.0027	-0.012	0.045*	-0.00016	-0.052***
	(-0.09)	(-1.10)	(1.61)	(0.05)	(-5.67)	(-0.32)	(-1.38)	(1.80)	(-0.01)	(-5.79)
Global × Crisis	-0.056	-0.054	-0.056	-0.074**	-0.053	-0.026	-0.026	-0.027	-0.038	-0.023
	(-1.53)	(-1.50)	(-1.55)	(-2.01)	(-1.54)	(-0.57)	(-0.57)	(-0.60)	(-0.84)	(-0.53)
Global × Crisis × Country fundamentals	-0.0028	0.012	-0.022	-0.011	0.023	-0.00018	0.024	-0.030	-0.025	0.020
	(-0.26)	(0.62)	(-1.18)	(-0.59)	(1.37)	(-0.02)	(1.03)	(-1.55)	(-1.24)	(1.00)
Local × Crisis	-0.081**	-0.081**	-0.080**	-0.082**	-0.099***	-0.025	-0.023	-0.026	-0.021	-0.059
	(-2.55)	(-2.57)	(-2.57)	(-2.48)	(-3.33)	(-0.61)	(-0.59)	(-0.62)	(-0.40)	(-1.37)
Local × Crisis × Country fundamentals	0.0061	-0.028	0.020	0.000038	-0.039	0.012	-0.031	0.011	-0.011	-0.063*
	(0.29)	(-0.96)	(0.47)	(0.00)	(-1.62)	(0.54)	(-0.80)	(0.21)	(-0.28)	(-1.77)
Crisis	-0.18*	-0.17*	-0.18*	-0.17*	-0.20**	-0.19	-0.18	-0.18	-0.088	-0.21
	(-1.69)	(-1.72)	(-1.72)	(-1.65)	(-2.00)	(-1.25)	(-1.28)	(-1.26)	(-0.64)	(-1.45)
Country fundamentals	-0.0034	-0.0052	0.0027	0.020	-0.013	-0.0071	-0.0050	0.0014	0.016	-0.015
	(-0.32)	(-0.43)	(0.18)	(1.14)	(-1.10)	(-0.67)	(-0.42)	(0.09)	(0.97)	(-1.32)
Crisis × Country fundamentals	-0.039	-0.0036	-0.050	-0.10	-0.073*	-0.013	-0.0083	-0.033	-0.16**	-0.058
	(-1.07)	(-0.07)	(-0.89)	(-1.54)	(-1.75)	(-0.31)	(-0.11)	(-0.47)	(-2.19)	(-1.03)
Adj. R-Square	0.00018	0.00019	0.00027	0.00018	0.00031	0.000049	0.000066	0.00014	0.000053	0.00017
N	12525780	12471769	12489366	11101006	12525780	12525780	12471769	12489366	11101006	12525780

Table 9 continued...

Panel B: Developing countries

	Global crisis VW 75%					Global crisis EW 66%						
	(1) Current Account	(2) Credit Rating	(3) FX Reserve	(4) Gov Budget	(5) Unemployment	(6) Current Account	(7) Credit Rating	(8) FX Reserve	(9) Gov Budget	(10) Unemployment	(11) est11	(12) est12
Global	-0.043	-0.041	-0.032	-0.033	-0.040	-0.044	-0.040	-0.038	-0.030	-0.031	-0.038	-0.042
	(-1.36)	(-1.33)	(-1.15)	(-1.26)	(-1.29)	(-1.37)	(-1.38)	(-1.33)	(-1.17)	(-1.24)	(-1.32)	(-1.39)
Local	-0.019	-0.031	-0.025	-0.026	-0.019	-0.019	-0.017	-0.027	-0.024	-0.024	-0.018	-0.016
	(-0.86)	(-1.29)	(-1.00)	(-1.06)	(-0.86)	(-0.77)	(-0.82)	(-1.19)	(-0.98)	(-1.04)	(-0.84)	(-0.69)
Global × Country fundamentals		-0.018	-0.049*	-0.030	-0.028	0.026*		-0.019	-0.049**	-0.030	-0.023	0.025**
		(-1.20)	(-1.95)	(-1.09)	(-1.59)	(1.95)		(-1.44)	(-2.04)	(-1.21)	(-1.43)	(2.01)
Local × Country fundamentals		-0.064***	-0.029*	-0.058**	0.011	-0.0064		-0.056***	-0.028*	-0.054**	0.0065	-0.0077
		(-3.49)	(-1.65)	(-2.32)	(0.89)	(-0.55)		(-3.28)	(-1.65)	(-2.20)	(0.56)	(-0.69)
Global × Crisis	-0.10*	-0.078	-0.10*	-0.058	-0.088	-0.11*	-0.16**	-0.13*	-0.14**	-0.093	-0.12*	-0.15**
	(-1.67)	(-1.31)	(-1.76)	(-1.02)	(-1.53)	(-1.70)	(-2.27)	(-1.87)	(-2.14)	(-1.40)	(-1.95)	(-2.24)
Global × Crisis × Country fundamentals		-0.075***	-0.085**	-0.10**	-0.037	0.047**		-0.087***	-0.13***	-0.13***	-0.077*	0.082***
		(-2.84)	(-2.16)	(-2.50)	(-1.05)	(2.00)		(-3.12)	(-3.14)	(-2.99)	(-1.93)	(2.93)
Local × Crisis	0.045	0.061	0.058	0.059	0.0024	0.041	0.054	0.072	0.060	0.092	-0.048	0.039
	(0.84)	(1.06)	(1.07)	(1.05)	(0.05)	(0.79)	(0.85)	(1.05)	(1.05)	(1.30)	(-0.79)	(0.67)
Local × Crisis × Country fundamentals		-0.0022	0.058	-0.022	0.067	-0.065*		-0.028	0.071	-0.061	0.15**	-0.082*
		(-0.05)	(1.53)	(-0.36)	(1.43)	(-1.73)		(-0.52)	(1.64)	(-0.90)	(2.26)	(-1.79)
Crisis	-0.24	-0.21	-0.23	-0.18	-0.26	-0.22	-0.39	-0.31	-0.37	-0.26	-0.41*	-0.38
	(-1.19)	(-1.12)	(-1.18)	(-1.00)	(-1.45)	(-1.07)	(-1.53)	(-1.28)	(-1.62)	(-1.12)	(-1.79)	(-1.50)
Country fundamentals		-0.0027	-0.0068	0.048	0.063*	0.029		0.0054	-0.0022	0.057	0.066**	0.022
		(-0.10)	(-0.18)	(1.07)	(1.95)	(1.28)		(0.21)	(-0.06)	(1.29)	(2.10)	(0.97)
Crisis × Country fundamentals		-0.029	-0.018	-0.089	-0.020	-0.089		-0.12	-0.13	-0.23	-0.081	0.00077
		(-0.26)	(-0.12)	(-0.58)	(-0.16)	(-0.97)		(-0.90)	(-0.77)	(-1.30)	(-0.57)	(0.01)
Adj. R-Square	0.00036	0.00100	0.00072	0.0011	0.00053	0.00053	0.00047	0.0011	0.00088	0.0013	0.00075	0.00066
N	4888557	4888037	4844634	4888557	4810756	4687031	4888557	4888037	4844634	4888557	4810756	4687031

Table 10: Equity market openness and contagion

This table reports the estimates for the contagion coefficient for Hypothesis III. *,**, and *** indicates statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by week.

Panel A: Developed countries

	Global crisis VW 75%			Global crisis EW 66%		
	(1)	(2)	(3)	(4)	(5)	(6)
Global × Crisis	-0.048	-0.046	-0.047	0.010	0.0091	0.0090
	(-1.16)	(-1.13)	(-1.20)	(0.19)	(0.17)	(0.18)
Local × Crisis	-0.073**	-0.075**	-0.077**	0.016	0.013	0.010
	(-2.10)	(-2.20)	(-2.26)	(0.31)	(0.25)	(0.20)
Crisis	-0.16	-0.17*	-0.18*	-0.14	-0.18	-0.19
	(-1.54)	(-1.73)	(-1.88)	(-1.01)	(-1.32)	(-1.44)
Global × Crisis × Portfolio equity	-0.019	-0.018	-0.017	-0.066	-0.064	-0.064
	(-0.55)	(-0.52)	(-0.47)	(-1.55)	(-1.45)	(-1.42)
Local × Crisis × Portfolio equity	0.013	0.015	0.019	-0.022	-0.018	-0.016
	(0.32)	(0.37)	(0.43)	(-0.38)	(-0.31)	(-0.26)
Crisis × Portfolio equity	-0.13	-0.11	-0.098	-0.16	-0.13	-0.11
	(-1.26)	(-0.99)	(-0.83)	(-1.17)	(-0.87)	(-0.72)
Global × Crisis × Size	-0.024		-0.010	-0.022		-0.015
	(-1.04)		(-0.36)	(-0.69)		(-0.41)
Local × Crisis × Size	0.013		0.0049	0.0041		-0.0066
	(0.80)		(0.21)	(0.18)		(-0.18)
Crisis × Size	0.19***		0.15**	0.29***		0.22**
	(3.40)		(2.03)	(3.61)		(2.52)
Global × Crisis × Portfolio equity × Size	0.011		0.0062	0.016		0.022
	(0.81)		(0.28)	(0.95)		(0.87)
Local × Crisis × Portfolio equity × Size	-0.016		-0.023	0.00083		-0.0059
	(-1.02)		(-0.93)	(0.04)		(-0.16)
Crisis × Portfolio equity × Size	0.053		-0.032	-0.0089		-0.084
	(1.10)		(-0.38)	(-0.17)		(-0.89)
Global × Crisis × Liquidity		-0.031*	-0.023		-0.021	-0.011
		(-1.81)	(-1.07)		(-0.90)	(-0.43)
Local × Crisis × Liquidity		0.013	0.012		0.014	0.020
		(0.62)	(0.43)		(0.41)	(0.42)
Crisis × Liquidity		0.17***	0.086		0.28***	0.14*
		(3.38)	(1.29)		(3.40)	(1.68)
Global × Crisis × Portfolio equity × Liquidity		0.014	0.0092		0.0055	-0.0087
		(0.93)	(0.40)		(0.33)	(-0.35)
Local × Crisis × Portfolio equity × Liquidity		-0.00040	0.012		0.0068	0.0094
		(-0.02)	(0.48)		(0.30)	(0.23)
Crisis × Portfolio equity × Liquidity		0.10**	0.12		0.042	0.090
		[illegible]	(1.40)		(0.64)	(0.84)
Adj. R-Square	0.0[illegible]	[illegible]32	0.00042	0.00027	0.00021	0.00031
N	125[illegible]	[illegible]780	12525780	12525780	12525780	12525780

Table 10 continued...

Panel B: Developing Markets

	Global crisis VW 75%			Global crisis EW 66%		
	(1)	(2)	(3)	(4)	(5)	(6)
Global × Crisis	-0.10*	-0.12*	-0.11*	-0.17**	-0.20**	-0.18**
	(-1.72)	(-1.91)	(-1.86)	(-2.33)	(-2.52)	(-2.44)
Local × Crisis	-0.015	-0.045	-0.035	-0.061	-0.10	-0.083
	(-0.33)	(-0.88)	(-0.74)	(-0.98)	(-1.45)	(-1.29)
Crisis	-0.28	-0.30	-0.29	-0.51*	-0.57*	-0.53*
	(-1.48)	(-1.43)	(-1.55)	(-1.87)	(-1.87)	(-1.91)
Global × Crisis × Portfolio equity	0.014	0.015	0.012	0.044	0.049	0.042
	(0.35)	(0.34)	(0.28)	(0.89)	(0.90)	(0.84)
Local × Crisis × Portfolio equity	0.12*	0.092	0.089*	0.17**	0.15**	0.14**
	(1.86)	(1.61)	(1.66)	(2.23)	(2.02)	(2.06)
Crisis × Portfolio equity	0.038	0.042	0.037	0.20	0.23	0.20
	(0.26)	(0.27)	(0.25)	(0.90)	(0.93)	(0.88)
Global × Crisis × Size	-0.084*		-0.065	-0.11**		-0.079*
	(-1.88)		(-1.52)	(-2.37)		(-1.78)
Local × Crisis × Size	-0.057		-0.055	-0.096*		-0.093**
	(-1.24)		(-1.40)	(-1.74)		(-2.09)
Crisis × Size	-0.054		-0.027	-0.22		-0.17
	(-0.37)		(-0.20)	(-1.11)		(-0.98)
Global × Crisis × Portfolio equity × Size	0.040		0.018	0.065**		0.038
	(1.44)		(0.62)	(2.12)		(1.20)
Local × Crisis × Portfolio equity × Size	-0.030		-0.051**	0.0092		-0.012
	(-1.31)		(-2.52)	(0.27)		(-0.44)
Crisis × Portfolio equity × Size	0.11		0.082	0.25**		0.21*
	(1.45)		(0.92)	(2.06)		(1.70)
Global × Crisis × Liquidity		-0.056*	-0.027		-0.10***	-0.063*
		(-1.72)	(-0.98)		(-2.62)	(-1.95)
Local × Crisis × Liquidity		0.012	0.032		0.0056	0.044
		(0.35)	(1.23)		(0.13)	(1.42)
Crisis × Liquidity		-0.048	-0.031		-0.18	-0.088
		(-0.42)	(-0.34)		(-1.10)	(-0.73)
Global × Crisis × Portfolio equity × Liquidity		0.063**	0.050*		0.083**	0.059*
		(2.24)	(1.75)		(2.40)	(1.68)
Local × Crisis × Portfolio equity × Liquidity		0.069*	0.081**		0.091*	0.086**
		(1.70)	(2.16)		(1.81)	(1.97)
Crisis × Portfolio equity × Liquidity		0.096	0.063		0.19	0.091
		.03)	(0.62)		(1.35)	(0.66)
Adj. R-Square	(	0094	0.0011	0.0012	0.0012	0.0014
N	4	8557	4888557	4888557	4888557	4888557

Table 11: Foreign credit reliance and contagion

This table reports the estimates for the contagion coefficient for Hypothesis IV. *,**, and *** indicates statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by week.

Panel A: Developed countries

	Global crisis VW 75%			Global crisis EW 66%		
	(1)	(2)	(3)	(4)	(5)	(6)
Global × Crisis	-0.070*	-0.072*	-0.070*	-0.045	-0.045	-0.045
	(-1.74)	(-1.91)	(-1.75)	(-0.86)	(-0.95)	(-0.87)
Local × Crisis	-0.077**	-0.076**	-0.077**	-0.0072	-0.0080	-0.0076
	(-2.24)	(-2.26)	(-2.27)	(-0.15)	(-0.17)	(-0.16)
Crisis	-0.22*	-0.20*	-0.23*	-0.18	-0.15	-0.20
	(-1.91)	(-1.75)	(-1.95)	(-1.16)	(-1.02)	(-1.25)
Global × Crisis × Foreign credit reliance	-0.015	-0.014	-0.014	-0.043	-0.042	-0.043
	(-0.52)	(-0.51)	(-0.50)	(-1.12)	(-1.09)	(-1.10)
Local × Crisis × Foreign credit reliance	0.0099	0.0083	0.0091	-0.047	-0.048	-0.048
	(0.27)	(0.23)	(0.26)	(-0.91)	(-0.93)	(-0.92)
Crisis × Foreign credit reliance	-0.12	-0.13*	-0.12*	-0.18*	-0.19*	-0.19*
	(-1.63)	(-1.72)	(-1.66)	(-1.76)	(-1.85)	(-1.82)
Global × Crisis × Size	-0.013		-0.014	-0.0085		-0.0091
	(-0.60)		(-0.65)	(-0.29)		(-0.32)
Local × Crisis × Size	0.016		0.018	0.015		0.016
	(0.96)		(1.06)	(0.71)		(0.71)
Crisis × Size	0.22***		0.23***	0.25***		0.27***
	(4.09)		(4.32)	(3.22)		(3.54)
Global × Crisis × Leverage		0.0045	0.0080		0.0077	0.0094
		(0.43)	(0.79)		(0.75)	(0.94)
Local × Crisis × Leverage		-0.011	-0.0099		0.0039	0.0031
		(-0.77)	(-0.73)		(0.20)	(0.16)
Crisis × Leverage		0.0042	-0.038		-0.062*	-0.12***
		(0.13)	(-1.22)		(-1.81)	(-3.55)
Global × Crisis × Foreign credit reliance × Size	-0.018		-0.018	-0.010		-0.010
	(-1.50)		(-1.52)	(-0.68)		(-0.66)
Local × Crisis × Foreign credit reliance × Size	-0.035***		-0.034***	-0.014		-0.012
	(-2.80)		(-2.76)	(-0.84)		(-0.78)
Crisis × Foreign credit reliance × Size	0.056*		0.060*	0.073**		0.086**
	(1.70)		(1.86)	(1.98)		(2.38)
Global × Crisis × Foreign credit reliance × Leverage		-0.0088	-0.0061		-0.013	-0.012
		(-0.85)	(-0.63)		(-1.25)	(-1.26)
Local × Crisis × Foreign credit reliance × Leverage		-0.00030	0.00053		-0.0079	-0.0081
		(-0.03)	(0.05)		(-0.67)	(-0.70)
Crisis × Foreign credit reliance × Leverage		0.0032	-0.018		0.020	-0.011
		(0.12)	(-0.72)		(0.69)	(-0.42)
Adj. R-Square		.00019	0.00038	0.00027	0.00010	0.00028
N		591086	9591086	9591086	9591086	9591086

Table 11 continued...

Panel B: Developing countries

	Global crisis VW 75%			Global crisis EW 66%		
	(1)	(2)	(3)	(4)	(5)	(6)
Global × Crisis	-0.12*	-0.16**	-0.11*	-0.18**	-0.23***	-0.17**
	(-1.80)	(-2.14)	(-1.73)	(-2.36)	(-2.72)	(-2.32)
Local × Crisis	-0.00072	-0.013	0.00074	0.010	-0.013	0.013
	(-0.01)	(-0.22)	(0.02)	(0.16)	(-0.19)	(0.21)
Crisis	-0.24	-0.24	-0.23	-0.41	-0.47	-0.40
	(-1.09)	(-0.97)	(-1.09)	(-1.41)	(-1.47)	(-1.43)
Global × Crisis × Foreign credit reliance	0.044	0.079	0.039	0.078	0.12**	0.073
	(1.02)	(1.48)	(0.92)	(1.58)	(2.01)	(1.53)
Local × Crisis × Foreign credit reliance	0.039	0.055	0.038	0.059	0.087	0.059
	(0.58)	(0.72)	(0.59)	(0.80)	(1.05)	(0.81)
Crisis × Foreign credit reliance	0.078	0.077	0.074	0.24	0.29	0.23
	(0.42)	(0.35)	(0.41)	(0.99)	(1.02)	(1.00)
Global × Crisis × Size	-0.080**		-0.080**	-0.087**		-0.087**
	(-2.20)		(-2.22)	(-2.32)		(-2.33)
Local × Crisis × Size	-0.054*		-0.053*	-0.067**		-0.067**
	(-1.70)		(-1.68)	(-2.19)		(-2.18)
Crisis × Size	0.014		0.014	-0.061		-0.060
	(0.13)		(0.13)	(-0.49)		(-0.48)
Global × Crisis × Leverage		-0.033**	-0.033**		-0.031**	-0.030**
		(-2.53)	(-2.58)		(-2.30)	(-2.30)
Local × Crisis × Leverage		0.0011	0.0014		-0.0011	-0.00093
		(0.08)	(0.10)		(-0.08)	(-0.07)
Crisis × Leverage		-0.025	-0.023		-0.020	-0.014
		(-0.55)	(-0.50)		(-0.42)	(-0.30)
Global × Crisis × Foreign credit reliance × Size	0.074**		0.073**	0.086***		0.086***
	(2.36)		(2.36)	(2.72)		(2.72)
Local × Crisis × Foreign credit reliance × Size	0.00085		-0.00016	0.018		0.017
	(0.03)		(-0.00)	(0.58)		(0.55)
Crisis × Foreign credit reliance × Size	0.036		0.034	0.13		0.12
	(0.36)		(0.34)	(1.14)		(1.13)
Global × Crisis × Foreign credit reliance × Leverage		0.024**	0.025**		0.021*	0.022*
		(2.00)	(2.17)		(1.75)	(1.88)
Local × Crisis × Foreign credit reliance × Leverage		0.012	0.011		0.016	0.014
		(0.93)	(0.84)		(1.22)	(1.11)
Crisis × Foreign credit reliance × Leverage		0.0058	0.00071		0.0031	-0.0015
		(0.14)	(0.02)		(0.07)	(-0.04)
Adj. R-Square	0.0021	0.0016	0.0021	0.0024	0.0019	0.0024
N	4888557	4888557	4888557	4888557	4888557	4888557

Appendix

A Variable Definition

Variable	Description
	Firm characteristics
Size	Firm market capitalization (MV) at the end of June.
Book to Market	The inverse of the ratio of Price to Book (WC09304) which is computed as the year-end market value of equity divided by book value of equity.
Leverage Ratio	The ratio of Total Debt (WC03255) to Total Assets (WC02999).
ROE	Return on equity (WorldScope item 08301).
Gross Profit	The Gross Income (WC01100), which is the difference between sales or revenues and cost of goods sold, depreciation, depletion and amortization, scaled by Total Assets (WC02999).
Liquidity	The fraction of trading days with nonzero return over the past year.
Earnings Volatility	The standard deviation of Earnings Per Share (WC05201) in the last five years divided by the average of EPS in the past five years.
Z-score	$6.56 * \frac{working\ capital}{total\ asset} + 3.26 * \frac{retained\ earnings}{total\ asset} + 6.72 * \frac{earnings}{total\ asset} + 1.05 * \frac{common\ equity}{total\ liability} + 3.25$, as in Altman et al (2016) Z”-score.
	Country characteristics
Size of the trade sector	Exports plus imports relative to GDP. Bilateral trade data are gathered from the IMF’s Direction of Trade Statistics.
Capital account openness	Schindler index. The index was initially introduced in Schindler(2009). It is based on the binary dummy variables that are coded at the level of resident/nonresident restrictions reported in the IMF’s Annual Report on Exchange Arrangements and Exchange Restrictions.
De facto Equity Market Integration	The total stock portfolio equity asset plus liabilities relative to GDP. The data is from Lane and Milesi-Ferretti (2007). All stock variables are measured as of Dec 31 and hence converted in USD at the end-of-period exchange rate.
Total borrowing form foreign banks (+)	Borrowing by all sectors of a particular country as a percentage of GDP. The data is from BIS consolidated banking statistics.

Figure 1: Pagan-Sossounov Bear Market Indicator

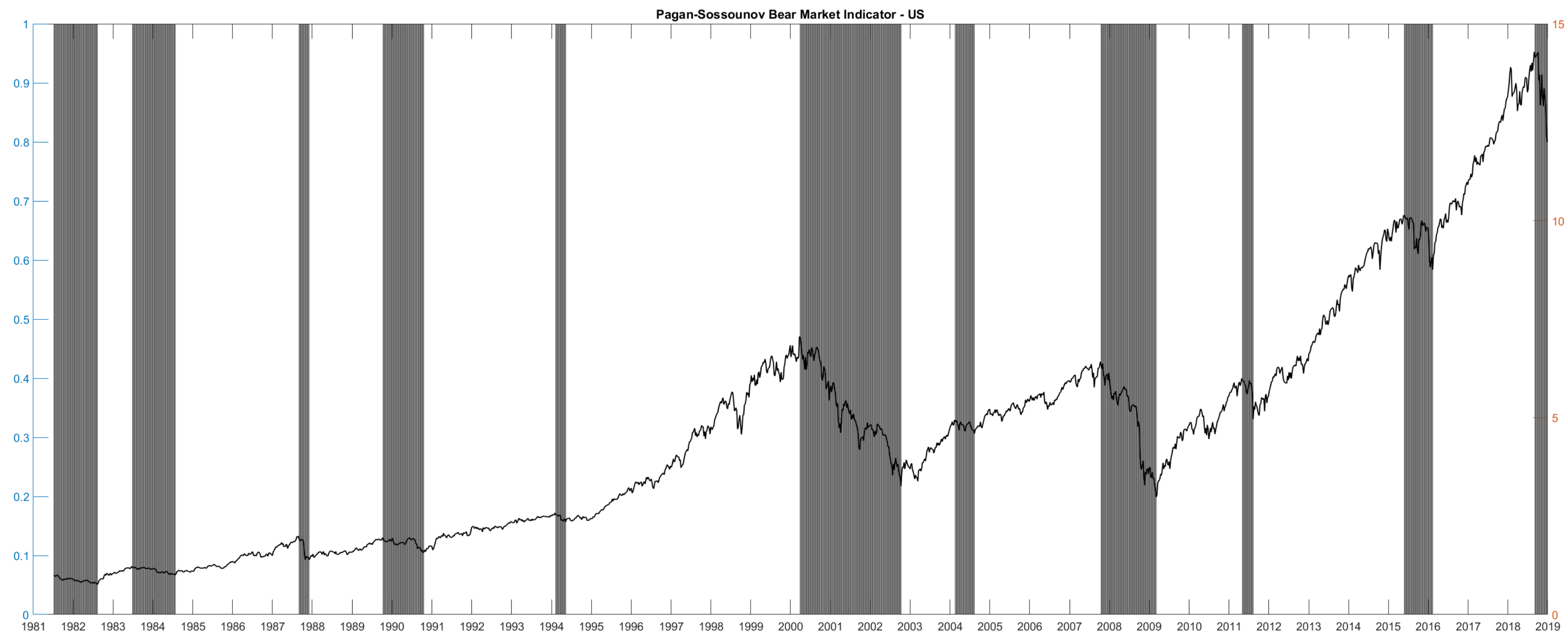
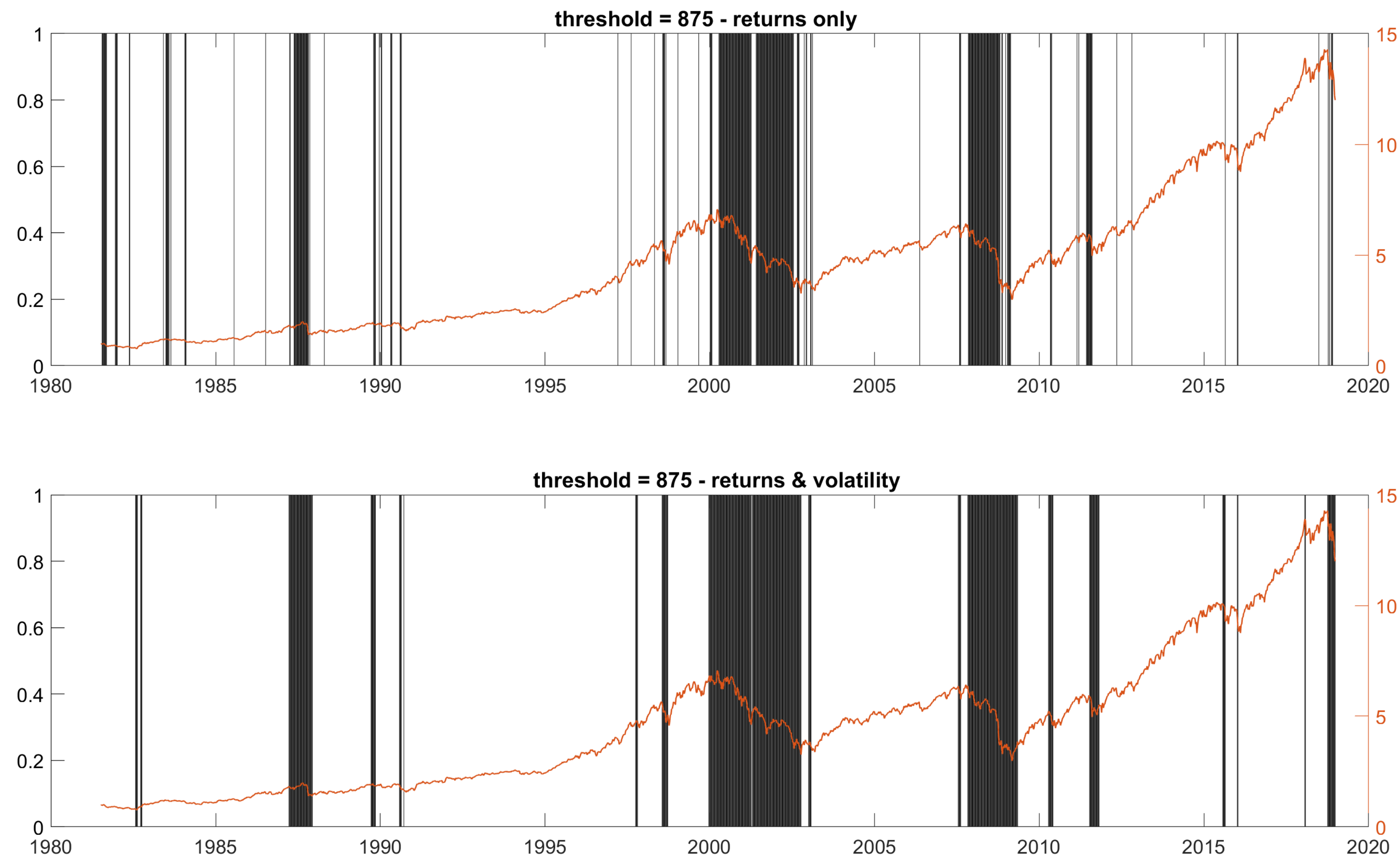


Figure 2: Crisis Dummy - Threshold level of 0.875



Chapter 3

Flight to Safety at High Frequency

1 Introduction

The last 30 years have witnessed many flights-to-safety (FTS, henceforth). FTS events are characterized by contemporaneous large drops in risky asset prices but large increases in safe asset values, as well as surging equity volatility and risk premiums (see e.g. Baele et al. (2019)). Existing work has predominantly identified FTS events using benchmark equity indices as a proxy for risky assets and top-rated Treasury bonds as a proxy for safe assets.[1] A recent example of an extreme FTS event occurred in the two days following the unexpected vote for Brexit, when the Euro Stoxx50 dropped with more than 11% while German 10-year bonds went up with nearly 2%. These events have substantial implications for risk management and portfolio allocation. It is thus important to understand what triggers FTS, how the market behaves around FTS episodes, and how FTS transmit across both countries and asset markets.

What differentiates this paper from previous work is the frequency of the data: Rather than using daily returns, we collect tick-by-tick data on equity index and government bond futures for 10 countries. This high-frequency dataset allows us to identify FTS events at a 5-minute frequency, which in turn enables us to answer a number of questions that studies using daily data cannot. First, we can identify the dynamics of an FTS within a single day. Second, we can dramatically reduce the list of all candidate FTS trigger events that occur during an FTS day to the ones occurring during or directly before a 5-minute FTS interval. Third, once the sources of FTS are identified, we can analyze in detail how FTS events transmit across markets. Again, this is not possible using daily data, as by the end of the day, all markets have absorbed the new information, and one cannot identify receiver and sender countries.

[1] Beber, Brandt, and Cen (2014) identify "risk-off" episodes based on correlations between foreign exchange returns; Bauer and Lucey (2010) additionally include gold as a potential safe asset.

Section 2 describes this high-frequency dataset in more detail. We obtain tick-by-tick data for equity index futures and 10-year government bond futures for seven developed markets (the US, the UK, Germany, Japan, Canada, Australia, and France) and three emerging markets (Brazil, Mexico, and South Africa) over the period 1996-2017. Starting dates are in the nineties for nearly all countries; even for Mexico, which has the shortest sample, we still have ten years of data. By including emerging markets in our sample, we can investigate to what extent FTS in developed markets are disruptive for emerging markets (and vice versa).

Section 3 introduces our FTS identification method, which is inspired by the co-exceedance measures of Bae et al. (2003) and Baele et al. (2019). In essence, we identify a 5-minute interval as an FTS when equity and bond futures returns scaled by their corresponding 250-day historical instantaneous (jump-robust) volatility (excluding the five most recent days) are respectively below and above a threshold level κ. In other words, during an FTS, equities should drop with at least κ times the trailing equity volatility, while Treasuries should at least increase with κ times the trailing bond volatility. A threshold level of $\kappa = 4$ works well in our application, but our results are robust to setting $\kappa = 3$ or $\kappa = 5$ as well. For all developed markets, we use the local Treasury bond as the safe benchmark. Because the local bond is typically not considered a safe asset for an emerging market country, we use the benchmark safe asset within the region (the US for Brazil and Mexico, Germany for South Africa) instead. When we set κ equal to four, 3.43% of US trading days experience at least one FTS. This value is close to the daily FTS incidence found in Baele et al. (2019) using a more involved approach. However, US FTS incidence is towards the upper bound across countries; trading days with FTS events are below 1% for Japan and Australia. Within a 5-minute FTS interval, equities drop in between 0.6% to 0.8%, while bonds increase with between 0.18% to 0.25%.

Section 4 characterizes our FTS events in more detail. We find that while most FTS days experience only one FTS event, about 10% of days experience two and 3% even three. We show that before and after FTS events, 5-minute return volatility is close to its unconditional average, much lower than the volatility during FTS intervals. Also, futures trading volumes increase drastically during an FTS event, but then immediately revert towards pre-FTS levels. The findings on volatility and trading volume suggest that FTS occur fast and tend to be short-lived.

Section 5 provides a first analysis of the triggers of FTS. At this time, we only examine US macroeconomic announcements as potential triggers. We use an extensive list of pre-scheduled macroeconomic news covering major news announcements widely considered in the existing literature. By counting the number of FTS that happen in the first five-minute interval following macro announcements, we find that the announcements of Employment Situation are an important trigger for FTS events. We also find that a significant portion of FTS across countries occur immediately after macro announcements. Thus, US macro announcements serve as an important trigger for FTS events not only for the US, but also for other countries.

Section 6 studies the transmission of FTS across countries. We report for each country the number of local FTS that occur during the same interval as US, German, or Japanese FTS, as well as the local bond and equity returns during these FTS events. We find that a large number of local FTS events overlap with US FTS events, with the percentage overlap ranging between 30% and 85%. Equity markets tend to experience abrupt declines and bond market substantial surges during the same five-minute interval, with the average magnitude close to or above the FTS threshold. Similar results are found for German FTS events. To investigate the transmission more formally, we estimate a Firthlogit model to quantify to what extent the occurrence of a high frequency FTS in a particular country increases the possibility of flight-to-safety in another country in the same 5-minute interval. The results show that FTS events transmit within regions, with the US being the sender for countries like Mexico, Brazil, and Canada, while Germany being the sender for countries in Europe and Africa. Moreover, during overlapping trading hours, there is strong evidence of global transmission from the US and Germany to other countries.

Finally, Section 7 studies if our results are robust to FTS events identified with 1-minute returns. We show that 1-minute FTS events are qualitatively similar to the 5-minute ones. Specifically, a substantial number of 1-minute FTS events occur immediately after US macro announcements, and FTS events from other countries tend to occur in the same one-minute intervals of US and German

FTS. However, we find that index futures are traded less frequently in developing countries than their developed country counterparts. Therefore, 1-minute frequency is less suitable for our study of FTS trigger and transmission.

This paper contributes to several related strands of literature. The literature on FTS has been advancing in both empirical and theoretical front. Early empirical work such as Connolly et al. (2005) and Baele et al. (2010) show that VIX and stock-bond illiquidity are associated with episodes of negative stock-bond return correlations. Our paper is closely related to Baele et al. (2019), which identify FTS using daily data from 23 countries since 1980 and conduct a systematic characterization of FTS. Our paper identifies FTS at a high frequency of five-minute and shows strong evidence of FTS transmission across countries. Also, the high-frequency identification enables us to study the importance of macroeconomic news announcements as a trigger of FTS.

Our results provide guidance to the theoretical literature on FTS. In Vayanos (2004)'s model, an increase in volatility leads to fears of redemption and higher risk aversion, which in turn give rise to flight-to-safety. Brunnermeier and Pedersen (2008) show that as volatility increases, margin requirements rise, causing not only a liquidity dry-up, but also a flight-to-quality, which they define as a sharp drop in liquidity provision for the high margin, more volatile assets. In the consumption-based asset pricing literature (e.g. Barsky (1989); Bekaert et al. (2009)) a flight-to-safety is typically defined as the joint occurrence of higher economic uncertainty (viewed as exogenous) with lower equity prices (through a cash flow or risk premium effect) and low real rates (through a precautionary savings effect). These papers stress the theoretical importance of volatility as a trigger of FTS. By examining realized volatility of equity futures, however, we find little evidence that FTS are related to an intraday increase in market uncertainty.

We contribute to the literature on the spillover effect in asset return and volatility. Earlier studies mostly focus on equity markets and use low-frequency data. Engle et al. (1994), King and Wadhwani (1990), Bae et al. (2003), Bekaert et al. (2005), Baele (2005), and Diebold and Yilmaz (2009) investigate return and volatility spillover effects cross international stock markets. Gande and Parsley (2005) study spillovers across government bond markets. A recent study by

Bongaerts et al. (2018) use high-frequency data on individual stocks and examine spillovers of jumps in prices, trading, and liquidity across equity markets. At a 5-minute frequency, they also find a strong spillover effect in prices between Europe and American markets. We contribute to the literature by analyzing the transmission of FTS events, where the movements in stock and bond prices have to be contemporaneous and in opposite direction.

Our study also contributes to the large literature that investigates the effect of macroeconomic announcements on asset prices. McQueen and Roley (1993) and Fleming and Remolona (1999) show that releases of major macroeconomic announcements lead to sharp and nearly instantaneous price changes in either the US Treasury bond market or equity market. Law et al. (2018) show that stock market responses to macro announcements depend on expectations about monetary policy. There are a few papers that conduct a joint analysis on stock and bond market reaction to macro announcements. Andersen et al. (2007) study responses to US macroeconomic news using 5-minute returns on equity and bond market. They show a time-varying stock-bond realized correlation on days with Non-farm Payroll announcement. Lahaye et al. (2011) link macro announcements to co-jumps in US equity index futures and Treasury 30 years futures. Our contribution to literature is to be the first to link macro announcements to the phenomenon of FTS, where stock and bond market not only move substantially, but with stock market moving downward and bond market moving upward. Also, our scope of analysis with 10 countries in the sample enables us to investigate the global FTS effect of US macro announcements.

2 Data

We obtain high-frequency data for equity index futures and 10-year government bond futures for 10 countries from Thomson Reuters Tick History. It includes transaction prices, trading volumes, bid and ask quotes and sizes for nearest-to-maturity (nearby) and second nearest-to-maturity (next) futures. Each observation is time-stamped to the nearest millisecond, which is the time that the message was transmitted by Reuters across its IDN real-time network. Our data cover seven developed markets (US, UK, Germany, Japan, Canada, Australia, and France) and six emerging markets (Brazil, Mexico, and South Africa). The sample period is from 8th January 1996 to 7th August 2017. Details of the futures contracts are relegated to Appendix Table A.1. We use equity index and government bond futures as price movements in these assets reflect market-wide shocks, so our FTS measure captures aggregate-level flights-to-safety.

We use the following steps to clean our data. First, we drop all observations outside trading hours, on the last trading days of each futures contract, or on exchange holidays. Second, we download daily high and daily low price for each contract from Datastream. High-frequency price observations that are higher than the daily high or lower than the daily low price are deleted. It turns out that the amount of deleted data is very small, less than 0.1% for most futures. The largest proportion is for Mexican IPC nearby futures contract, which is 3.88%. It confirms the statement by Liu et al. (2015) that the data provided by Thomson Reuter's Tick History, especially the data on futures, is very clean compared with the more widely used NYSE TAQ data. We construct liquidity-maximum continuous futures series using nearby and next futures contracts. We roll over from the nearby to the next contract on the day when there are more trades in the next contract than the nearby contract. Although many contracts have long trading hours, we trim the intraday sample to focus on the period when the cash stock market is open. Exceptions include the US and Canada where the intraday sample start from 8:00 a.m. ET, as many US macro announcements are released at 8:30 a.m. ET. We refer to Appendix Table A.2 for details.

We calculate the five-minute interval return as

$$r^i_{t,j} = p^i_{t,j} - p^i_{t,j-1},$$

where $p^i_{t,j}$ is the log price at the end of five minute interval j for future i at day t. If the last millisecond observed in a five-minute interval corresponds to several price observations, then the last observation is used to calculate returns. We explicitly exclude overnight returns. The intraday return over each day's first five-minute interval is calculated as the log difference between the last and the first observed price within the first interval. Our choice of the 5-minute frequency balances the need to avoid market microstructure noise and the need to obtain high-frequency observations. Previous literature that also uses a five-minute frequency includes Andersen et al. (2007), Tauchen and Zhou (2011), Liu et al. (2015), and Bongaerts et al. (2018). We delete a trading day if a futures contract has fewer than 36 observations on that day, which means less than three hours of trading. The Mexican equity index futures sample only starts in 2007 as it has very few return observations until then. For other futures contracts, this threshold of a minimum of 36 observations per day has little impact on sample size.

Panel A of Table 1 reports the summary statistics of 5-minute returns in percentage. Average returns on bond futures are positive and close to 0.0001% except for Australia and Canada. German government bond futures have the highest average return, consistent with the decline in the long-term yield in the Euro area during the past ten years. Within equity futures, developed countries all have negative average returns. The finding is consistent with studies such as Cliff et al. (2008) and Lou et al. (2019), which have shown that US equity premium is mainly due to overnight returns, and returns during the day are close to zero or even negative. Among emerging markets, Mexico has a positive average return. Brazilian equity index futures have the highest return standard deviation of 0.19%, more than double the level of Australia, which has the lowest volatility among equity futures. The last two columns report the 1th and 99th percentile of five-minute returns. For each instrument, the absolute magnitude of the 1st percentile return is similar to that of the 99th percentile, suggesting the distribution of log returns is mostly symmetric.

3 Measures of Flight to Safety

3.1 Methodology

Our methodology of identifying FTS is inspired by the co-exceedance measures of Bae et al. (2003) and Baele et al. (2019). In particular, we define an FTS as a five-minute interval during which the standardized bond futures return is above a threshold while at the same time the standardized stock index futures return is below a certain threshold:

$$FTS^i_{t,j} = I\{z^{i,B}_{t,j} > \kappa\} \times I\{z^{i,S}_{t,j} < -\kappa\}, \tag{1}$$

$$z^{i,m}_{t,j} = r^{i,m}_{t,j} / \sigma^{i,m}_{t-1},\ m = B\ or\ S, \tag{2}$$

$$\sigma^{i,m}_t = \sqrt{\frac{1}{245 \times n - 1} \times \frac{\pi}{2} \sum_{\tau=6}^{250} \sum_{j=2}^{n} |r^{i,m}_{t-\tau,j}||r^{i,m}_{t-\tau,j-1}|}\ ,\ m = B\ or\ S, \tag{3}$$

where I is indicator function, $r^{i,B}_{t,j}$ and $r^{i,S}_{t,j}$ is the bond or equity index futures returns at 5-minute interval j at day t in country i. $\sigma^{i,B}_{t-1}$ and $\sigma^{i,S}_{t-1}$ are referred to as instantaneous volatility estimator of bond and stock futures returns, respectively, based on five-minute returns in the past 250 days excluding the nearest 5 days. The long window results in a slow-moving instantaneous volatility estimator which is not affected by transitory large market swings. n is the total number of return observations on each day. τ is a particular day, ranging from $t-250$ to $t-6$. The volatility estimation is robust to the presence of jump (see Bajgrowicz et al. (2015), Barndorff-Nielsen and Shephard (2006)). κ is the number of standard deviations the bond and equity returns need to be above and below zero, respectively, before an interval is identified as an FTS. We impose the same threshold to both equities and bonds. We refer to $z^{i,m}_{t,j}$ as scaled returns as they are scaled by volatility.

Panel B of Table 1 reports summary statistics of annualized estimated instantaneous volatilities of intraday returns. Unsurprisingly, the volatility of bond futures returns is much lower than that of equity futures returns. Australia equity futures have the lowest average volatility among all equity futures, while Brazil's equity futures are the most volatile. The annualized volatility of US equity futures is 14.92%, close to the counterpart of the UK, Japan, and South Africa, and slightly lower than those of Germany and France.

Table 2 reports summary statistics of scaled returns where each 5-minute return is scaled by its instantaneous volatility. Note that the 1st and 99th percentiles for all futures are around -3 and 3, respectively, somewhat higher than what would be implied by the normal distribution. The standard deviation of the scaled returns is higher than one across all futures, confirming that there is a jump component in price dynamics not captured by the measure of instantaneous volatility.

For the US, the UK, Germany, Australia, Japan, and Canada, an FTS is defined as from the domestic equity market to the domestic bond market. However, we define an FTS in Brazil, Mexico, and South Africa as from the domestic equity market to the benchmark bond market in the same region: US for Brazil and Mexico, Germany for South Africa. The reason is that the government bonds of these emerging countries are not considered safe assets, especially not during stress times. For France, which does not have domestic bond futures contracts, we also use German bonds as the benchmark safe asset.

3.2 The choice of threshold

The choice of the threshold of κ is inevitably ad hoc. To examine the effect of different threshold levels, we calculate the incidence of FTS and return impact for κ's ranging from 2 to 6. Figure 1 reports the percentage of FTS days and the corresponding return impact across countries. When κ increases, as shown in the graph, FTS incidence decreases while average return impact, defined as bond minus equity return over the five-minute FTS interval, increases. For the US, FTS days constitute 25% of trading days when the threshold is 2, and the percentage declines sharply to 8% when κ goes up to 3. The average 5-minute return impact of FTS is around 0.4% when $\kappa = 2$, and rises to 1.2% when $\kappa = 6$.

Table 3 shows how the number and percentage of FTS observations within different countries varies with different levels for κ. Panel A shows that, when $\kappa = 4$, about 3.5% of US trading days experience at least one FTS episode. This value is similar to the daily FTS incidence found in Baele et al. (2019) using a more involved approach. A similar FTS incidence is found in France and Germany. Asian developed markets Australia and Japan have fewer FTS events, with the percentage to be below 1%. For emerging markets, South Africa experiences FTS on around 2% of trading days, while Brazil and Mexico's percentage of trading days are 1.33% and 1.03%, respectively. Equity and bond return impact is more comparable across countries. The decrease in the equity market during the FTS 5-minute interval ranges mostly from 0.6% to 0.8%. The increase in the bond market also mainly varies from 0.18% to 0.25%. A notable exception is Australia where the return is as low as 0.03%.

Two specific FTS events in our sample are as follows. On June 4th 2010, after the release of the May 2010 Employment Situation, there is FTS during the interval from 8:30 E.T. to 8:35 E.T in Brazil, Canada, Germnay, France, South Africa, UK, US. According to the Wall Street Journal [2], "Analysts were disappointed by the low level of jobs created in the private sector, the worst figure since January and well below the median projection". On August 8th, 2011, fearful investors reacted to the United States losing its AAA credit rating at the night of Friday August 5th . Our data shows that there is FTS event from 10:25 to 10:30 ET in US, and the same time in Germany, France, and South Africa.

Panels B and C of Table 3 show corresponding summary statistics for levels of κ equal to 3 and 5, respectively. When $\kappa = 3$, the US witnesses FTS on around 8% of trading days. During a typical FTS episode, the equity market goes down by 0.49% while the bond market goes up by 0.18%. With $\kappa = 5$, there are around 2% trading days that experience FTS, and the equity market impact increases to -0.76%. Germany has 7.50% of trading days that experience FTS for $\kappa = 3$. The return impact is -0.56% on the equity market and 0.13% on the bond market, similar to those on the French market. A further rise in κ to 5 decreases the percentage of both countries to around 1.8%. In comparison, Australia observes less incidence of FTS, as the percentage of trading days with FTS is 1.68% when $\kappa = 3$, to 0.15% for $\kappa = 5$. Among emerging markets, about 5% of tradings days in South Africa are identified as FTS days when $\kappa = 3$, but only 0.89% when $\kappa = 5$.

Overall, the analysis above indicates that $\kappa = 4$ balances FTS incidence and return impact well. In what folows, we will use this threshold level, but check the robustness of our results to alternative levels.

[2]https://www.wsj.com/articles/SB10001424052748704764404575286263535019280

3.3 Lagged FTS

Our results show that there tend to be fewer FTS events in emerging markets, irrespective of what threshold level is used. We now investigate to what extent this lower FTS incidence is simply caused by a slower reaction of emerging equity markets to (global) FTS news. More specifically, the liquid benchmark bond may react immediately to a FTS at interval T, while the less liquid emerging equity market may only react in the subsequent 5-min interval $T+1$. We identify these additional ‘lagged’ FTS events in the following way:

$$Lagged\ FTS_{t,j}^{i} \quad = \quad I\{z_{t,j}^{i,B} > \kappa\} \times I\{z_{t,j}^{i,S} >= -\kappa\} \times I\{z_{t+1,j}^{i,S} < -\kappa\}. \tag{4}$$

We present the results for $\kappa = 4$ in Table 4. The first column repeats the number of days with FTS events defined as in Equation (1) with $\kappa = 4$. The second column reports the number of days with lagged FTS events, defined as in Equation (4). The number of lagged FTS events are in general much lower than the benchmark FTS events. In particular, both Brazil and South Africa have more than 60 FTS days, but only around 15 lagged FTS days. Mexico has 15 lagged FTS events and 23 FTS events, so the relative importance of lagged FTS events is higher than in other countries. Overall, however, considering lagged stock market returns has limited impact on our FTS measure.

3.4 5-min FTS vs daily FTS

Do the days featuring 5-minute FTS events overlap with days featuring daily FTS events identified in Baele et al. (2019)? We compare the two type of days using the daily FTS dummy from Baele et al. (2019). We drop our data after 5th July 2015, which is the ending point of their sample period. Also, as Brazil, Mexico, and South Africa are not included in their sample, the comparison concentrates on developed countries.

The results are presented in Table 5. It turns out that for the US, there are 36 days with both 5-min FTS and daily FTS events, and 127 days with only 5-minute events. In other words, around 20% of 5-min FTS days also feature daily FTS events. The proportion is similar in Canada, France, Germany, and the UK. Meanwhile, the Japanese market has only two days that feature both types of FTS events while Australia has none. Apart from different identification methodology, one potential reason for the relatively low overlapping is that many daily FTS events are probably driven by overnight returns, which are excluded in our sample. We will analyze these overnight returns and their FTS incidence in future versions of this paper.

4 Characterization of FTS

This section provides a systematic characterization of high-frequency FTS. Section 4.1 investigates to what extent FTS days exhibit multiple FTS 5-minute intervals. Sections 4.2 and 4.3 characterize realized volatility and trading volume, respectively, before, during, and after FTS events.

4.1 Cluster of FTS events

Table 6 reports the percentage of days that have one, two, and three FTS. Although the majority of FTS days experience one flight-to-safety, there is clear evidence of FTS clustering. For example, the US has in total 174 FTS days, 78% of them witness one FTS, while 13% witness two FTS, and 6% have three events. The number of days with multiple FTS events are much higher than what is implied by independence between occurrences of FTS. Countries also vary in the degree of FTS clustering. Germany and France have a higher percentage of one-FTS days than the US, but the days with two FTS are both around 9% out of total FTS days, much lower than the 13% of the US. Emerging markets tend to have a lower degree of clustering. More than 86% of the FTS days across emerging markets have only one FTS event.

4.2 Realized Volatility around FTS

How does the volatility dynamics in futures market evolve around FTS events? Figure 2 plots for each country the median and inter-quartile range of volatility, measured by the absolute value of 5-minute scaled returns, for each five-minute interval around FTS. We follow Heston et al. (2010)

in using the absolute value of returns as volatility proxy. In particular, for every five minute from the third before the FTS interval (T-3) until the third after the FTS interval (T+3), we calculate the median and inter-quartile of absolute scaled return on equity futures and bond futures across FTS events of a particular country. We also plot the unconditional mean over the whole sample as the benchmark. We observe a notable pattern across countries and both equity and bond markets: a substantial increase in the magnitude of absolute return from T-1 to T, and a sharp decrease from T to T+1. Meanwhile, the volatility from T-3 to T-1 and from T+1 to T+3 remains rather stable, and close to the unconditional mean. Note that equity market volatility seems to be slightly elevated after FTS compared to pre-FTS level. This is not surprising as an FTS involves a strong negative stock return, which is known to raise subsequent volatility (the leverage effect). Table 7 presents the mean absolute scaled returns. As it shows, German stock market volatility stays around 2 from T-3 to T-1, jumps to 7.36 at FTS episode, declines sharply at T+1 to 2.62, and remains around 2.5 from T+2. An emerging market example is South Africa stock market, with volatility lower than 2 from T-3 to T-1, increases substantially to 6.15 at flight episode T, then decreases abruptly to below 2 at T+1.

In sum, by examining and comparing volatility before and after FTS events, Figure 2 clearly shows that FTS intervals experience much larger market swings than pre- and post-FTS 5-minute intervals. The difference suggests again that FTS occurs fast and tend to be short-lived. Moreover, as stock market scaled returns are small at T+1, it confirms the previous result that considering lagged stock returns have a limited impact on our identification of FTS events.

4.3 Trading volume around FTS

Are flights-to-safety accompanied by substantial trading volumes? The answer to this question would not only help to understand the drivers of FTS, but also provide valuable guidance to theoretical models. To this end, we study trading volume patterns around FTS episodes. The high-frequency futures data not only enable us to identity FTS during each five-minute interval, but also allow us to examine trading behavior at the same frequency. Therefore, we can identify the link between FTS and tradings, which is not possible using daily data.

Table 8 shows the trading volume on equity index futures and bond futures in the five-minute interval before, during, and after FTS. Column T-3 presents the trading volume during the third five-minute interval preceding FTS episodes, while Column T+3 presents the trading volume during the third five-minute interval following FTS episodes. Almost all countries show the same pattern that within an FTS interval, the trading volume doubles or even quadruples (as in Japan equity futures) compared to the pre-FTS level. In the next 15 minutes or three intervals, however, trading volumes decrease dramatically, though not necessarily back to pre-FTS levels. For example, the trading volume of US equity futures goes from 33,465 contracts at T-1 to 64,048 contracts at T, and back to 37,446 contracts at T+3.

In sum, the results show that our identified FTS are associated with substantial investor trading in both equity and bond markets, suggesting the important role of investor re-balancing in flights-to-safety. After the episode, trading volumes decline toward pre-FTS levels quickly, indicating that FTS do happen quickly and finish within five minutes.

4.4 The persistence of FTS

Do markets recover after FTS? Figure 3 reports the average cumulative return on equity and bond futures over intervals following FTS events. It shows that there is reversal in equity and bond returns following the FTS interval, though the degree is far from fully offsetting the return impact of FTS events. For example, the return impact of US FTS on equity market is on average around -0.7%, but within the following 90 five-minute intervals, the equity market recovers by 0.3%, suggesting that part of the FTS impact is driven by market liquidity and therefore only transitory. Similar patterns are also observed for other countries except Canada and Japan. In future version of the paper, we will investigate the role of liquidity in more details.

5 FTS Triggers

5.1 Macro news announcements and FTS

Previous sections suggest that FTS events are accompanied by substantial trading volume and tend to be short-lived. These results indicate that information events may have an important role in driving FTS events. In this section, therefore, we investigate the extent to which FTS are caused by US pre-scheduled macro news announcements (MNAs), using a comprehensive set of macro announcements listed in Table A.3. Note that most of the announcements are released at 8:30 a.m. ET and 10:00 a.m. ET. Although US and Brazil stock cash market is closed at 8:30 ET, the futures markets are already open. Also, the Europe and South Africa markets are still open at 8:30 ET and 10:00 ET. This overlap allows us to study how many of the FTS events in those regions occur immediately after macro announcements. Studies such as Andersen et al. (2007) and Bollerslev et al. (2018) have shown that US stock and bond futures exhibit a robust and consistent response to the surprises of some announcements. Moreover, Andersen et al. (2007) document that the mere presence of an announcement, besides the size of the corresponding surprise, tends to increase volatility. Therefore, instead of linking FTS to announcement surprises, we count the number of FTS following macro announcements.

Panel A of Table 9 reports the total number of FTS events during the first and second five-minute interval after macro announcements. In total, 77 FTS events in the US happen within ten minutes after macro announcements, among all 233 US FTS events. Furthermore, 68 out of these 77 FTS events occur during the first 5-minute interval after announcements, indicating that these FTS events are not only caused by macro announcements, but also within a rather tight window after announcements. The Brazilian market experiences 26 FTS events within ten minutes after US announcements, with 24 of them in the first five minutes. Similarly, there are 74 French FTS during the ten minutes after announcements, and 71 of them happen within the first five minutes, showing that US macro announcements also serve as an important trigger for FTS events in Europe.

Panel B of Table 9 reports the top 10 announcements with the largest number of FTS during the first 5-minute interval after the announcement. Across different countries, Employment Situation, Construction Spending, ISM Manufacturing, Consumer Confidence, and Initial Jobless Claims tend to occupy the top of the lists. These announcements are also shown in the literature (see Law et al. (2018) and Kurov et al. (2019)) to have a significant and robust impact on stock and bond markets. 26 announcements of the Employment Situation are followed by an FTS in the US during the following five minutes. In Germany and France, more than 20 FTS events happen within 5 minutes after announcements of Employment. In Brazil and South Africa, the job reports also play a major role, causing 12 and 14 FTS events, respectively. The number of FTS events in Germany, France, UK and US following ISM Manufacturing, Construction Spending, Consumer Confidence, and Initial Jobless Claims is roughly 1/3 of those following Employment Situation. However, these four announcements are less important in driving FTS in other countries. The Mexican market seems not affected by US macro announcements. Note that the top ten announcements lead to a similar number of FTS in Germany and France as in the US, indicating a global nature of FTS, which is examined closely in the next section.

Panel C of Table 9 reports the top 10 announcements that are most likely to trigger FTS events during the second five-minute interval. Consistent with Panel A, few FTS occur during this episode. For example, only one FTS in the US happens over the second five minutes after Employment Situation. One exception is FOMC, where three FTS from the US happen during the second interval. These FOMC announcements are on 14:15 December 11th, 2007, 14:00 January 28th, 2015, and 14:00, January 27th 2016, respectively.

5.2 Other triggers of FTS

Future versions of this paper will also investigate other potential triggers of FTS, such as macroeconomic announcements outside the US, the role of (unexpected) monetary policy decisions (such as unexpected rate decisions or disappointing announcements related to quantitative easing), political risk realizations (most recently, the vote for a Brexit and the ongoing Trade War), or large industry or firm shocks (think of failure of a specific bank). Following Bongaerts et al. (2018), we will also investigate the role of liquity shocks as potential triggers for FTS. As signaled above, we will not only consider news event during but also outside trading hours.

6 FTS transmission across countries

Now that we have analyzed and characterized FTS events in high frequency, a natural question to ask is whether these events coincide in various countries. Given the short-lived nature of FTS events, zooming in at 5-minutes interval gives a sharper view of FTS spillovers. Therefore, this section studies the spillover effect of FTS across international markets. We first report country-specific equity and bond market returns, as well as the number of FTS during FTS episodes from the US, Germany, and Japan. Then we use Firthlogit model to examine if the occurrence of a high-frequency FTS event in a particular country increases the possibility of observing a FTS in another country in the same 5-minute interval.

6.1 Co-occurrence of FTS event across countries

Panel A of Table 10 reports the average equity and bond scaled returns on the intervals that US FTS happen as well as the three intervals thereafter. If FTS events are country-specific and have no overlap, then the average returns should be close to zero. However, the first column shows that the equity scaled return is in general lower than -4 across countries at time T, which is the threshold of FTS. Therefore, the equity markets in non-US countries also witness abrupt declines when FTS occur in the US. For instance, Germany and France experience an average equity scaled return as low as around -6.5. The scaled return on equity decreases by -5.61 on average in the UK. Canada and South Africa also have a decline by -4.75. However, the equity price decline seems to be limited to the exact interval T when US FTS occurs. When moving to the next interval T+1, the decrease in equity scaled returns is much smaller in magnitude, which is generally lower than 0.5. Similar results hold for T+2 and T+3, suggesting that the impact of US FTS to other countries happen very fast.

The next four columns report bond scaled returns. Note that Mexico and Brazil are assigned with US bond market. Therefore it is not surprising to observe large bond price surges. However, for Canada, Germany, France, UK, and South Africa, the bond returns are in general higher than 4.5 at the time when a US FTS happens. In contrast, the next three columns show that following scaled returns are close to zero, suggesting that the increase in bond prices concentrates on the 5-minute interval with US FTS.

Panel B reports the number of FTS that happen on the same five-minute interval with a US FTS. Remarkably, for Brazil, 68 out of 81 FTS events coincide with US FTS events. The proportion for Mexico is also high, with 18 out of 26 events happening during the same interval as in the US. Similarly, Canada experiences 47 FTS in total, 33 of them occur simultaneously with US ones. The results strongly indicate a regional, if not global, nature of FTS. As regards countries in Europe, the UK, Germany, and France have around one-third of the FTS coinciding with US FTS, which is also a significant proportion. South Africa has 75 FTS events, and almost half of them occur at the same interval as the US. Some FTS happen in the five-minute intervals after an episode of US FTS, though the cases are rare. For example, three out of the total 211 Germany FTS happen during the five minutes next to a US episode. Overall, Table 10 suggests that FTS events in the US tend to immediately trigger FTS events in other countries.

Next, we conduct a similar analysis on German FTS events, given the status of the German market in Europe and Africa. Panel A of Table 11 reports the average equity and bond scaled returns on German FTS intervals and the three intervals after. German FTS also immediately trigger a sharp equity market decline and bond market surge in other countries. For example, the average equity scaled return in the UK is as low as -5.74 at T, but become -0.13 at T+1. Panel B show that around 80% of French and South Africa FTS happen at the same five-minute interval as a German FTS. In the British market, the proportion is lower but still more than 50%. Furthermore, the coincidence is less likely for the US, Canada, Mexico, and Brazil. The disparity suggests the existence of regional FTS that affect particularly Germany, France, UK, and South Africa. However, few FTS from these European countries happen at the intervals after a German FTS, which suggests that the transmission of German FTS is also very fast across European countries.

Table 12 shows the impact of Japanese FTS on Australia, the only country that has overlapping trading hours with Japan. Surprisingly, only 2 of the 34 Australian FTS happen at the same interval as Japanese FTS. The absence of transmission suggests that FTS events in Asia are country-specific.

6.2 Explaining flight-to-safety by US and German FTS

After showing the coincidence of FTS events across countries, we now examine how FTS events transmit from the US or Germany to other countries. In particular, we examine if the probability of occurrence of FTS in a particular country can be explained by FTS events from the US and Germany. We follow Bongaerts et al. (2018) in using Firthlogti model, which entails penalized maximum likelihood estimation. Heinze and Schemper (2002) show that Firthlogit model instead of regular Logit model overcomes the "separation problem" when events of interest are rare. The dependent variable is an indicator variable of whether there is an FTS event at a particular 5-minute interval in country i. For independent variables, we use indicator variables of FTS events in the US and/or Germany at the same 5-minute interval, and an indicator variable of whether there exist announcements on Employment Situation, ISM Manufacturing, Construction Spending, Consumer Confidence, and Initial Jobless Claims at the beginning of the five-minute interval.

Table 13 presents the marginal effects of the Firthlogit models. The results in Panel A are consistent with previous findings that US FTS events trigger FTS in other countries. Moreover, the effects are both economically and significantly substantial, especially for European countries: A US FTS occurrence increases the probability of FTS events by 48% in France and Germany, and around 34% in the UK and South Africa. In particular, without US FTS, the unconditional probability of occurrence of UK FTS is $1/(1+exp(8.98)) = 0.01\%$, with -8.98 as the intercept in the Firthlogit model. With US FTS incidence, the probability of UK FTS becomes $1/(1+exp(8.98-8.31)) = 33.85\%$ where 8.31 is the coefficient on US FTS. The difference is the marginal effect $33.85\% - 0.01\% = 33.84\%$. The high intensity of transmission is not surprising given that the overlapping trading hours between the US and Europe are on the morning in Eastern Time when many US announcements are released. In contrast, Mexico and Canada seem to be less affected by US FTS, with the probability only increases by 16% and 18% when US FTS happen.

Panel B includes the indicator of the presence of macro announcement $MNA = 1$ or 0. It captures the triggering effect of macro announcements on FTS events in both US and other countries. So the marginal effect on US FTS is not compounded by macro announcements. The marginal effect is estimated at the mean of independent variables. Estimating at $MNA = 0$ leads to a similar result. The inclusion of announcements reduces the marginal effect of US FTS events, especially for European countries and South Africa. For example, the marginal effect of a US FTS on France decreases from 48.1% to 36.4% with a lower t-value. This is consistent with the earlier discussion that the high intensity of transmission in Panel A is partially due to releases of announcements. For Canada and Brazil, the decrease is no more than 2%, much smaller in comparison. The little change suggests that the transmission of FTS from the US to Canada and Brazil is not much associated with macro announcements.

Panel C studies if German FTS events transmit to other countries. The independent variables are the indicator of German FTS events and the indicator of macro announcements. The marginal effect is also estimated at the mean. Notably, a German FTS increases the probability of FTS events by 80.6% in France, and by 30.6% in South Africa. The comparison between Panel B and Panel suggests that Brazil, Canada, and Mexico are more affected by US FTS events. Meanwhile, France and South Africa are more affected by German FTS events. For the US, the probability increase is also as high as 38.8% when an FTS happens in Germany, similar to the coefficient of 36.7% on US FTS events for Germany. It makes it challenging to make inference on the transmission direction between the two countries, and suggests that global FTS events (those that co-occur in the US and Germany) comprise a similar share in US and German FTS events during the overlapping trading hours. A simple counting confirms the idea. In particular, in the sample during overlapping hours, there are in total 76 FTS events that happen at the same interval in both countries, 82 US FTS events not triggering German ones, and 76 German FTS events not triggering US ones.

The fact that many German and US FTS events tend to happen at the same interval compounds the transmission estimation from the US and Germany to other countries. Therefore, Panel D presents the model where independent variables include both indicator variables for US and German FTS events, as well as the indicator of macro announcements. The results show that after controlling for German FTS events, the marginal effect of US FTS events becomes close to zero for France and South Africa, and decreases to 4.62% for the UK, compared to Panel B where the marginal effects for there three countries are higher than 20%. Meanwhile, the marginal effects of Germany FTS on American countries are also all close to zero, in contrast to the results from Panel C. However, the effect of US (Germany) events on Brazil, Canada, and Mexico (France, UK, South Africa) remains similar as in Panel B (C). The results indicate a dominant role played by the US and Germany in regional FTS transmission in American and Europe/Africa, respectively. Moreover, the US and Germany FTS co-co-occurrence from Panel B and C plus their role in regional transmission suggests global FTS transmission from the US and Germany to other countries. Note that the effect of macro announcements is not significant anymore, suggesting that the trigger effect of announcements on these countries is captured by the transmission of FTS from the US and Germany.

Overall, Table 13 suggests that first, FTS events transmit within regions, with the US being the sender for countries like Mexico, Brazil, and Canada, while Germany being the send for countries in Europe and Africa. Second, during the overlapping trading hours, there is strong evidence of global transmission of FTS events from the US and Germany to other markets.

7 Robustness

Table 14 reports the robustness of our results when FTS events are identified by 1-minute equity and bond returns. Panel A of Table 14 shows that with $\kappa = 4$, most countries have much more 1-minute FTS events compared to the 5-minute ones. In an unreported table, I find that the 1th percentile and 99th percentile of the scaled returns is also close to 3, similar to the 5-minute scaled returns. Therefore, as the frequency changes from 5-minute to 1-minute, a larger amount of observations mechanically leads to more identified FTS events. The only exception is Mexico. The reason is that Mexico's equity index futures are not traded frequently enough. As a result, many one-minute returns are simply missing. The results also suggest that to obtain a similar percentage of FTS days, using a higher frequency of returns requires a higher threshold of κ. We will use κ equal to 5 even higher in the future version of the paper.

Panel B of Table 14 investigates if macro announcements still serve as a trigger of 1-minute FTS events. It turns out a substantial number of 1-minute FTS events occur immediately after macro announcements. Panel C focuses on the robustness of FTS transmission across countries to 1-minute returns. Similar to the case of five minute, the UK, Germany, and France have around one-third of the FTS coinciding with US FTS. However, a lower proportion of Brazilian and Canadian FTS events co-occur with US. Instead, a significant amount of FTS events in these two countries happen in T+1, the one-minute interval after an episode of US FTS. Overall, the results still confirm the fast nature of transmission of FTS events. Panel D of Table 14 shows that about 80% of French and South Africa FTS, and over 50% of British FTS happen at the same one-minute interval as a German FTS, the proportion also similar to the five-minute case. Finally, Panel E conduct the same Firthlogit analysis for 1-minute FTS events. Consistent with the results from Panel C, the coefficient on US FTS is lower and less significant for both UK and Canada. On the other hand, the coefficient on German FTS has a higher magnitude and/or becomes more significant for the UK, France, and South Africa.

In summary, the overall results of 1-minute FTS events are qualitatively similar to the 5-minute ones. However, given the fact that index futures in developing countries are traded less frequently than their developed country counterparts, 1-minute frequency is less suitable for our study.

8 Conclusion

Using high-frequency data on equity index and government bond futures returns, we identify 5-minute FTS episodes in 10 countries during which bond returns are positive while at the same time equity returns are large and negative. On average, 5-minute FTS events comprise less than 4% of the sample days, and when they occur, equities drop within the 5-min interval with 0.6% to 0.8%, while bonds increase with 0.18% to 0.25%. FTS events tend to be short-lived and associated with high trading volume. While realized volatility surges during FTS, it is not particularly high before or after FTS intervals. We document that many FTS are triggered by US macroeconomic announcements and provide first evidence on how FTS transmit globally.

This first version of our paper represents only a first analysis of FTS at high frequency. We have in mind several avenues for future research. First of all, we will not only consider Flight-to-Safety (or 'Risk-Off') events, but also the opposite Flight-to-Risk (FTR, or 'Risk-On') events. Second, we will not only analyze intraday 5-min intervals, but also overnight returns, as we now realize that many FTS events already occur at market opening. Third, we will analyze the behavior of implied volatility on equities (e.g. the VIX) and bonds around FTS/FTR. Fourth, and most importantly, we will analyze a much broader set of triggers for both FTS and FTR, possible using text-based news measures. Finally, we intend to link our FTS/FTR transmission model better to the existing theoretical literature on crisis transmission.

Table 1: Summary statistics for 5-minute returns and instantaneous volatility

This table reports summary statistics of 5-minute returns and annualized instantaneous volatility for each country. Returns are in percentage. Instantaneous volatility is based on 5-minute returns in the past 250 days excluding the nearest 5 days.

Panel A: 5-minute returns

	Mean	Std	1th	99th
Developed Countries				
Australia 10-Year Gov Bond	0.00002	0.01	-0.02	0.02
Canada 10-Year Gov Bond	0.00003	0.04	-0.10	0.09
Germany 10-Year Gov Bond	0.00013	0.03	-0.08	0.08
Japan 10-Year Gov Bond	0.00011	0.03	-0.07	0.07
UK Long Gilt	0.00009	0.04	-0.10	0.09
US 10-Year T-note	0.00011	0.04	-0.10	0.09
Australia ASX 200	-0.00046	0.08	-0.22	0.22
Canada TSX60	-0.00018	0.11	-0.32	0.31
France CAC 40	-0.00029	0.12	-0.34	0.32
Germany FDAX	-0.00032	0.12	-0.36	0.34
Japan Nikkei 225	-0.00037	0.13	-0.37	0.36
UK FTSE 100	-0.00041	0.10	-0.29	0.28
US E-mini S&P500	-0.00007	0.11	-0.31	0.30
Emerging Markets				
Brazil Ibovespa	-0.00024	0.19	-0.52	0.50
Mexico IPC	0.00026	0.13	-0.38	0.39
SouthAfrica JSE 40	-0.00030	0.10	-0.29	0.28

Table 1: Continued

Panel B: Annualized instantaneous volatility

	Mean	Std	1th	99th
Developed Countries				
Australia 10-Year Gov Bond	0.56	0.12	0.30	0.84
Canada 10-Year Gov Bond	4.50	0.86	2.52	6.25
Germany 10-Year Gov Bond	4.33	1.07	1.68	6.85
Japan 10-Year Gov Bond	2.58	1.03	1.01	5.36
UK Long Gilt	5.18	1.09	3.20	7.79
US 10-Year T-note	4.88	1.25	2.80	8.23
Australia ASX 200	9.68	3.39	2.68	19.50
Canada TSX60	13.81	5.93	3.70	33.39
France CAC 40	17.01	5.91	8.08	31.70
Germany FDAX	17.42	6.82	4.73	34.72
Japan Nikkei 225	14.89	3.79	5.02	25.26
UK FTSE 100	14.12	5.57	4.08	30.56
US E-mini S&P500	14.92	6.26	6.86	35.71
Emerging Markets				
Brazil Ibovespa	25.33	8.27	8.09	48.41
Mexico IPC	12.92	4.82	4.53	25.80
SouthAfrica JSE 40	14.43	5.00	3.39	28.26

Table 2: Summary statistics for 5-minute scaled return

This table reports summary statistics of scaled returns where five-minute interval returns are scaled by instantaneous volatility based on five-minute returns in the past 250 days excluding the nearest 5 days.

	Mean	Std	1th	99th
Developed Countries				
Australia 10-Year Gov Bond	0.00403	1.14	-2.80	2.81
Canada 10-Year Gov Bond	0.00115	1.08	-2.78	2.68
Germany 10-Year Gov Bond	0.00444	1.07	-2.90	2.75
Japan 10-Year Gov Bond	0.00435	1.11	-3.02	2.92
UK Long Gilt	0.00223	1.07	-2.88	2.78
US 10-Year T-note	0.00309	1.08	-2.79	2.68
Australia ASX 200	-0.00573	1.10	-2.97	2.89
Canada TSX60	-0.00133	1.11	-2.98	2.92
France CAC 40	-0.00206	1.07	-2.97	2.87
Germany FDAX	-0.00213	1.10	-3.12	2.95
Japan Nikkei 225	-0.00294	1.10	-2.88	2.86
UK FTSE 100	-0.00415	1.08	-3.01	2.89
US E-mini S&P500	-0.00051	1.07	-2.97	2.95
Emerging Markets				
Brazil Ibovespa	-0.00102	1.06	-2.87	2.79
Mexico IPC	0.00179	1.07	-2.96	2.97
SouthAfrica JSE 40	-0.00269	1.06	-2.93	2.79

Table 3: FTS instance and return

This table reports the number and percentage of days that flights-to-safety occurs. FTS are identified by indicator equation (1). Equity (Bond) 5-minute returns (in percentage) during FTS intervals are reported.

Panel A: $\kappa = 4$

	# of FTS days	% of FTS days	Equity 5-min ret	Bond 5-min ret
Developed Countries				
Australia	18	0.44	-0.46	0.03
Canada	41	0.94	-0.63	0.23
France	179	3.79	-0.69	0.18
Germany	166	3.06	-0.75	0.18
Japan	38	0.73	-0.69	0.13
UK	103	1.91	-0.63	0.20
US	174	3.51	-0.65	0.24
Emerging Markets				
Brazil	66	1.33	-0.92	0.25
Mexico	23	1.03	-0.80	0.22
South Africa	65	2.15	-0.55	0.19

Panel B: $\kappa = 3$

	# of FTS days	% of FTS days	Equity 5-min ret	Bond 5-min ret
Developed Countries				
Australia	68	1.68	-0.36	0.02
Canada	123	2.81	-0.48	0.17
France	400	8.47	-0.54	0.13
Germany	407	7.50	-0.56	0.13
Japan	134	2.57	-0.51	0.09
UK	307	5.69	-0.45	0.15
US	390	7.87	-0.49	0.18
Emerging Markets				
Brazil	192	3.87	-0.76	0.17
Mexico	58	2.60	-0.65	0.17
South Africa	151	5.00	-0.44	0.15

Table 3: Continued

Panel C: $\kappa = 5$

	# of FTS days	% of FTS days	Equity 5-min ret	Bond 5-min ret
Developed Countries				
Australia	6	0.15	-0.72	0.03
Canada	19	0.43	-0.78	0.30
France	88	1.86	-0.80	0.21
Germany	87	1.60	-0.88	0.21
Japan	12	0.23	-0.90	0.20
UK	51	0.94	-0.75	0.26
US	92	1.86	-0.76	0.29
Emerging Markets				
Brazil	30	0.60	-1.05	0.35
Mexico	6	0.27	-1.02	0.35
South Africa	27	0.89	-0.65	0.24

Table 4: FTS with lagged stock market

This table reports the number of days that FTS and lagged FTS occur. FTS are determined by indicator equation (1). Lagged FTS are determined by indicator equation (4).

	# of FTS days	# of lagged FTS days	# of days with lagged FTS but not FTS
Emerging Markets			
Brazil	66	16	10
Mexico	23	15	9
South Africa	65	15	13

Table 5: Daily FTS and 5-minute FTS

This table reports the total number of days that have daily FTS events, the number of days that have 5-minute FTS events, the number days that have both daily FTS and 5-minute FTS, as well as the number of days that have only one of the two FTS events. Daily FTS data is from Baele et al. (2019). The sample period ends at 5th July 2015 as in Baele et al. (2019).

	# of Daily FTS days	# of 5-min FTS days	# of days with both FTS	# of days with only daily FTS	# of days with only 5-min FTS
Australia	83	14	0	83	14
Canada	83	39	7	76	32
France	142	172	38	104	134
Germany	177	161	37	140	124
Japan	71	31	2	69	29
UK	185	97	25	160	72
US	209	163	36	173	127

Table 6: FTS cluster

This table reports the total number of FTS days for each country and the percentage of FTS days that have one, two, three FTS events. FTS events are identified with threshold $\kappa = 4$.

	# of FTS days	% of FTS days with 1 FTS	% of FTS days with 2 FTS	% of FTS days with 3 FTS
Developed Countries				
Australia	18	77.8	5.6	5.6
Canada	41	85.4	14.6	0.0
France	179	84.9	8.9	3.9
Germany	166	83.7	9.0	4.8
Japan	38	73.7	15.8	10.5
UK	103	84.5	9.7	3.9
US	174	78.7	13.2	6.3
Emerging Markets				
Brazil	66	86.4	6.1	6.1
Mexico	23	87.0	13.0	0.0
South Africa	65	89.2	7.7	1.5

Table 7: FTS and market volatility

This table reports the mean absolute scaled return on equity futures and bond futures around FTS. The five-minute interval when FTS occur is denoted as T. The first, second, and third five-minute interval before (after) the FTS interval are denoted as T-1, T-2, T-3 (T+1, T+2, T+3). Scaled returns are calculated as five-minute interval returns divided by instantaneous volatility based on five-minute returns in the past 250 days excluding the nearest 5 days. Panel A reports the volatility of equity index futures. Panel B reports the volatility of bond futures.

Panel A: Mean absolute return on equity index futures

	T-3	T-2	T-1	T	T+1	T+2	T+3
Developed Countries							
Australia	1.87	2.68	2.58	6.01	2.98	2.79	3.45
Canada	1.72	1.84	2.72	6.86	3.06	2.72	2.44
France	1.98	1.77	1.90	6.92	2.73	2.38	2.51
Germany	2.32	2.10	2.28	7.36	2.62	2.50	2.66
Japan	2.27	2.15	2.51	6.76	3.20	2.09	2.94
UK	1.88	1.87	2.66	7.61	3.02	2.86	2.71
US	1.66	1.97	2.40	7.12	2.73	2.63	2.23
Emerging Markets							
Brazil	1.78	1.90	1.56	6.39	2.25	2.30	2.38
Mexico	1.14	1.73	1.67	6.49	2.28	2.03	1.95
South Africa	1.92	1.54	1.86	6.15	1.96	1.79	1.88

Panel B: Mean absolute return on bond futures

	T-3	T-2	T-1	T	T+1	T+2	T+3
Developed Countries							
Australia	2.20	2.74	2.51	5.97	2.39	3.01	2.61
Canada	1.25	0.95	1.82	6.96	2.71	1.72	1.81
France	1.59	1.49	1.66	6.63	1.86	1.77	1.72
Germany	1.65	1.59	1.74	6.56	2.04	1.86	1.85
Japan	2.15	2.30	2.28	6.47	2.61	2.46	2.31
UK	1.47	1.41	1.81	6.60	2.05	1.92	1.59
US	1.34	1.45	2.21	7.24	2.49	2.05	1.79
Emerging Markets							
Brazil	1.37	1.74	1.99	7.67	2.52	2.50	1.85
Mexico	1.40	1.37	2.90	7.11	2.87	2.82	2.38
South Africa	1.29	1.11	1.93	6.67	1.82	1.72	1.36

Table 8: Trading around FTS

This table reports the trading volumes of futures contracts around FTS. The five-minute interval when FTS occur is denoted as T. The first, second, and third five-minute interval before (after) the FTS interval are denoted as T-1, T-2, T-3 (T+1, T+2, T+3). Panel A reports the trading volume on equity index futures. Panel B reports the trading volume on the bond futures of each country or the bond futures assigned to a country.

Panel A: Equity index futures

	T-3	T-2	T-1	T	T+1	T+2	T+3
Developed Countries							
Australia	824	867	862	1167	989	860	861
Canada	283	240	295	447	439	348	284
France	1949	2183	2075	5299	4109	3329	3260
Germany	1899	2105	2108	5541	4195	3341	3171
Japan	2996	3196	3081	5623	4193	3072	2758
UK	1623	1690	1819	4038	3095	2649	2447
US	27149	29164	33465	64048	50676	41181	37446
Emerging Markets							
Brazil	750	836	800	2055	1352	1025	929
Mexico	47	44	34	54	59	66	67
South Africa	426	421	432	1001	795	609	567

Panel B: Bond futures

	T-3	T-2	T-1	T	T+1	T+2	T+3
Developed Countries							
Australia	1506	1586	1799	2217	2007	1576	1558
Canada	427	421	399	696	610	506	481
France	12391	12035	12283	37373	26664	20325	17996
Germany	12200	11929	12538	35932	26691	20063	18159
Japan	961	887	1075	1666	1152	849	796
UK	1443	1383	1507	3478	2741	2258	1712
US	12939	14159	16458	40217	30769	23614	20980
Emerging Markets							
Brazil	15215	17127	17401	51823	36513	29901	25609
Mexico	17105	17879	27668	51229	38882	32081	29254
South Africa	11730	10807	12318	37453	25138	18637	17068

Table 9: Macro announcements and FTS

This table reports the number of FTS events that are triggered by US macroeconomic announcements. Panel A presents the total number of FTS events, the number of FTS events that occur within the first five-minute interval and second five-minute interval after macro announcements. Panel B and C list the number of FTS for each of the top ten macro announcements over the first and second five-minute interval, respectively.

Panel A: FTS after macro announcements

	# of FTS	First 5-minute	Second 5-minute
Brazil	81	24	2
Canada	47	11	2
France	223	71	3
Germany	211	64	4
Mexico	26	2	1
South Africa	75	31	1
UK	129	35	2
US	233	68	9

Panel B: FTS over the first 5-minute interval after each announcement

	BR	CA	DE	FR	MX	SA	UK	US
Employment	12	6	24	22	0	14	19	26
Construction Spending	2	0	7	8	0	4	6	9
ISM Manufacturing	2	0	8	9	0	4	7	9
Initial Jobless Claims	2	0	7	7	0	1	1	7
Consumer Confidence	0	1	8	8	0	1	2	7
Advanced Retail Sales	2	1	7	5	0	4	4	6
Durable Goods Orders	1	1	7	6	0	1	0	4
GDP Advance	1	0	5	4	0	1	2	3
Personal Income	1	0	1	1	0	2	1	2
Leading Economic Index	1	1	3	2	1	2	1	2

Panel C: FTS over the second 5-minute interval after each announcement

	BR	CA	DE	FR	MX	SA	UK	US
FOMC	0	1	0	0	0	0	0	3
Initial Jobless Claims	1	0	1	1	0	1	1	1
Factory Orders	1	1	0	0	0	0	0	1
Employment	0	0	0	0	1	0	1	1
ISM Non Manufacturing	0	0	0	0	0	0	0	1
Industrial Production	0	0	0	0	0	0	0	1
Consumer Confidence	0	0	0	0	0	0	0	1
ISM Manufacturing	0	0	2	2	0	0	0	0
Construction Spending	0	0	2	2	0	0	0	0
UM Consumer Sentiment	0		0	1	0	0	0	0

Table 10: FTS spillover from the US

This table reports across countries the average scaled return on equity and bond futures at and after US FTS intervals, as well as the number of FTS occurring at and after US FTS intervals. The five-minute interval when US FTS occur is denoted as T. Panel A reports the average scaled equity return and bond return for each country from T to T+3. Panel B presents for each country the total number of FTS, and the number of FTS occurring at T to T+3.

Panel A: Equity and bond scaled returns during and after US FTS interval

	Equity Ret				Bond Ret			
	T	T+1	T+2	T+3	T	T+1	T+2	T+3
Brazil	-3.53	-0.25	0.51	0.05	7.37	-0.43	-0.41	-0.09
Canada	-4.25	-0.34	0.32	0.25	4.51	0.32	-0.35	0.02
France	-6.37	-0.20	-0.09	-0.29	5.65	0.18	-0.01	0.04
Germany	-6.77	-0.17	0.05	-0.46	5.67	0.16	-0.00	0.02
Mexico	-2.05	-1.20	-0.05	-0.27	6.33	-0.43	-0.33	-0.16
South Africa	-4.75	-0.45	-0.06	0.06	5.45	-0.13	-0.00	0.23
UK	-5.61	-0.28	0.09	-0.25	4.81	0.08	-0.27	0.15

Panel B: Number of FTS during and after US FTS interval

	# of FTS	T	T+1	T+2	T+3
Brazil	81	68	4	5	3
Canada	47	33	3	0	0
France	223	76	4	4	2
Germany	211	76	3	4	2
Mexico	26	18	1	1	1
South Africa	75	34	1	2	0
UK	129	54	4	1	2

Table 11: FTS spillover from Germany

This table reports across countries the average scaled return on equity and bond futures at and after Germany FTS intervals, as well as the number of FTS occurring at and after Germany FTS intervals. The five-minute interval when Germany FTS occur is denoted as T. Panel A reports the average scaled equity return and bond return for each country from T to T+3. Panel B presents for each country the total number of FTS, and the number of FTS occurring at T to T+3.

Panel A: Equity and bond scaled returns during and after Germany FTS interval

	Equity Ret				Bond Ret			
	T	T+1	T+2	T+3	T	T+1	T+2	T+3
Brazil	-3.26	-0.53	0.40	-0.32	6.82	-0.08	-0.06	0.25
Canada	-3.52	-0.64	0.09	0.02	4.41	0.46	-0.06	0.03
France	-6.58	0.01	-0.22	-0.48	6.56	-0.03	-0.01	0.21
Mexico	-1.65	-0.62	-0.08	-0.35	5.40	-0.54	0.15	0.12
South Africa	-3.82	-0.41	-0.15	-0.22	6.40	-0.19	0.08	0.32
UK	-5.74	-0.13	0.04	-0.52	4.91	0.28	-0.10	0.15
US	-5.80	-0.19	0.16	-0.07	6.76	-0.03	-0.03	0.30

Panel B: Number of FTS during and after Germany FTS interval

	# of FTS	T	T+1	T+2	T+3
Brazil	81	33	1	2	4
Canada	47	8	1	0	0
France	223	177	5	4	9
Mexico	26	4	2	0	1
South Africa	75	55	0	2	2
UK	129	70	8	1	5
US	233	76	6	2	4

Table 12: FTS spillover from Japan

This table reports across countries the average scaled return on equity and bond futures at and after Japan FTS intervals, as well as the number of FTS occurring at and after Japan FTS intervals. The five-minute interval when Japan FTS occur is denoted as T. Panel A reports the average scaled equity return and bond return for each country from T to T+3. Panel B presents for each country the total number of FTS, and the number of FTS occurring at T to T+3.

Panel A: Equity and bond scaled returns during and after Japanese FTS interval

	Equity Ret				Bond Ret			
	T	T+1	T+2	T+3	T	T+1	T+2	T+3
Australia	-1.69	-0.08	-0.49	0.44	1.63	0.00	0.22	-0.30

Panel B: Number of FTS during and after Japanese FTS interval

	# of FTS	T	T+1	T+2	T+3
Australia	34	2	1	0	0

Table 13: Firthlogit models of FTS events

This table presents the marginal effects of the firthlogit models. Panel A reports the Firthlogit model where the independent variable is an indicator variable of US FTS events. Panel B reports the model where independent variables are indicators of both US FTS events and macro announcements of Employment Situation, ISM Manufacturing, Construction Spending, Consumer Confidence, and Initial Jobless Claims. Panel C reports the results where the independent variables are indicators of both German FTS events and macro announcements. Panel D reports the results where the independent variables include German and US FTS event indicators and the indicator variable of macro announcements. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

Panel A: The effect of US FTS events

	(1) BA	(2) CA	(3) DE	(4) FR	(5) MX	(6) SA	(7) UK
FTS US	0.342***	0.181***	0.481***	0.481***	0.162***	0.328***	0.340***
	(10.21)	(6.39)	(12.13)	(12.13)	(4.70)	(7.16)	(9.09)
N	388490	345651	200303	192498	150870	92511	202760

Panel B: The effect of US FTS events

	(1) BA	(2) CA	(3) DE	(4) FR	(5) MX	(6) SA	(7) UK
FTS US	0.329***	0.168***	0.367***	0.364***	0.170***	0.215***	0.250***
	(8.89)	(5.78)	(8.62)	(8.60)	(4.72)	(4.82)	(6.42)
MNA	0.0000501	0.000111	0.00241**	0.00303**	-0.0000964	0.00171*	0.000713**
	(0.83)	(1.13)	(2.74)	(2.82)	(-0.76)	(2.31)	(2.60)
N	388490	345651	200303	192498	150870	92511	202760

Panel C: The effect of German FTS events

	(1) BA	(2) CA	(3) FR	(4) MX	(5) SA	(6) UK	(7) US
FTS DE	0.177***	0.0378*	0.806***	0.0994*	0.306***	0.267***	0.388***
	(4.84)	(2.02)	(27.28)	(2.23)	(7.39)	(8.13)	(8.77)
MNA	0.000573*	0.00170	0.00124	-0.0000103	0.000631*	0.000595**	0.00611**
	(2.07)	(1.53)	(1.45)	(-0.02)	(2.23)	(2.64)	(3.29)
N	213155	124271	472150	52944	270363	526409	200303

Table 13: Continued

Panel D: The effect of US and German FTS events

	(1) BA	(2) CA	(3) FR	(4) MX	(5) SA	(6) UK
FTS US	0.242^{***}	0.192^{***}	0.00482	0.193^{**}	0.00115^{*}	0.0462^{*}
	(4.84)	(3.92)	(0.91)	(3.25)	(2.01)	(2.18)
FTS DE	0.000302^{*}	-0.0000976	0.713^{***}	0.0000192	0.148^{**}	0.00370
	(2.25)	(-1.11)	(13.04)	(0.10)	(2.81)	(1.95)
MNA	-0.00000189	0.000248	0.00106	-0.000206	0.000648	0.000393
	(-0.02)	(1.27)	(1.24)	(-0.96)	(1.71)	(1.69)
N	180551	121926	188650	52278	91361	197222

Table 14: Robustness of 1-minute FTS events

This table reports the robustness of 1-minute FTS events. Panel A reports the number and percentage of days that 1-minute FTS events occur. FTS are identified by indicator equation (1). Equity (Bond) 1-minute returns (in percentage) during FTS intervals are reported. Panel B reports the number of 1-minute FTS events that are triggered by US macroeconomic announcements. Panel C reports the spillover of FTS from US. Panel C reports the spillover of FTS from Germany. Panel E reports the marginal effects of the firthlogit models.

Panel A: FTS instance and return

	# of FTS days	% of FTS days	Equity 1-min ret	Bond 1-min ret
Developed Countries				
Australia	37	0.93	-0.19	0.02
Canada	69	2.09	-0.31	0.10
France	440	9.32	-0.33	0.10
Germany	442	8.15	-0.36	0.10
Japan	74	1.42	-0.37	0.05
UK	304	5.71	-0.29	0.11
US	398	8.03	-0.31	0.14
Emerging Markets				
Brazil	183	3.79	-0.44	0.15
Mexico	3	1.15	-0.42	0.09
South Africa	159	5.31	-0.28	0.11

Panel B: FTS after macro announcements

	# of FTS	First 1-minute	Second 1-minute
Brazil	246	89	7
Canada	106	16	3
Germany	678	156	17
France	695	156	15
Mexico	4	0	0
South Africa	201	66	3
UK	451	91	11
US	669	156	24

Panel C: Number of FTS during and after US FTS interval

	# of FTS	T(US)+0	T(US)+1	T(US)+2	T(US)+3
Australia	53	0	0	0	0
Brazil	246	179	21	8	11
Canada	106	48	12	5	8
Germany	678	214	5	6	7
France	695	221	9	5	9
India	9	0	0	0	0
Japan	112	0	0	0	0
Mexico	4		0	0	0
South Africa	201		2	3	3
UK	451		9	4	8

Table 14: Continued

Panel D: Number of FTS during and after German FTS interval

	# of FTS	T(DE)+0	T(DE)+1	T(DE)+2	T(DE)+3
Australia	53	0	0	0	0
Brazil	246	100	6	5	6
Canada	106	28	3	0	4
France	695	555	22	17	19
India	9	0	0	0	0
Japan	112	0	0	0	0
Mexico	4	2	1	0	0
South Africa	201	150	7	6	5
UK	451	242	25	15	16
US	669	214	12	11	12

Panel E: The effect of US and German FTS events

	(1)	(2)	(3)	(4)	(5)	(6)
	BA	CA	FR	MX	SA	UK
FTS US	0.172***	0.0208	0.0258*	0.0841	0.000363**	0.00811**
	(6.44)	(1.92)	(2.50)	(1.29)	(3.15)	(3.11)
FTS DE	0.000265***	0.000855	0.697***	0.000409	0.201***	0.0359***
	(3.80)	(1.74)	(23.45)	(0.97)	(6.10)	(3.49)
MNA	0.000249**	0.0000964	0.000461	0.0224	0.000529**	0.000317
	(3.02)	(1.02)	(1.69)	(0.74)	(2.77)	(1.93)
N	826606	433662	929534	26936	444523	963933

Figure 1: 5-minute FTS vs Kappa

This figure shows the percentage of FTS days out of total trading days and corresponding average return impact across countries and thresholds of κ. The return impact is calculated as bond return minus equity return over the 5-minute interval when FTS are identified.

Panel A: Developed Countries

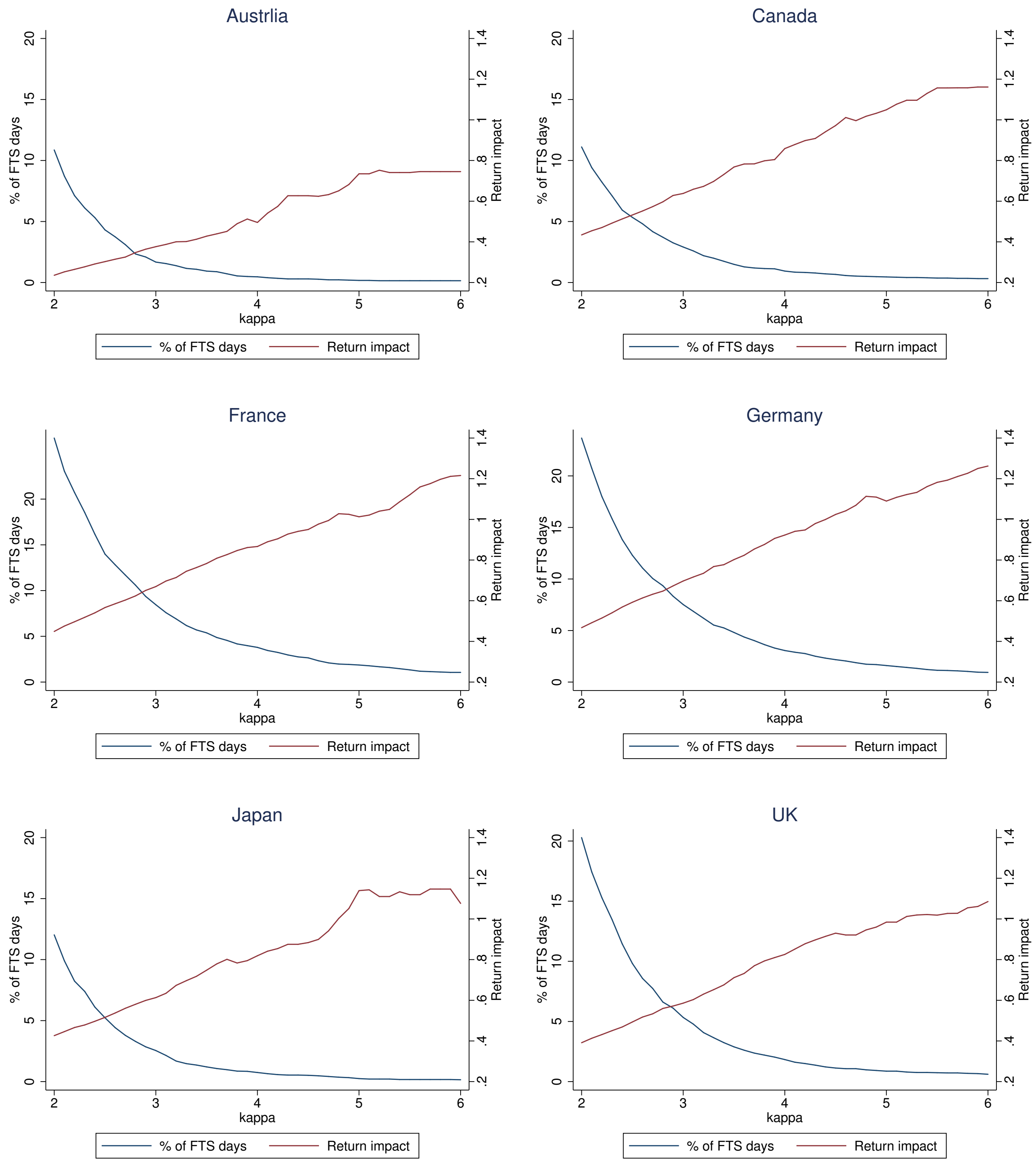
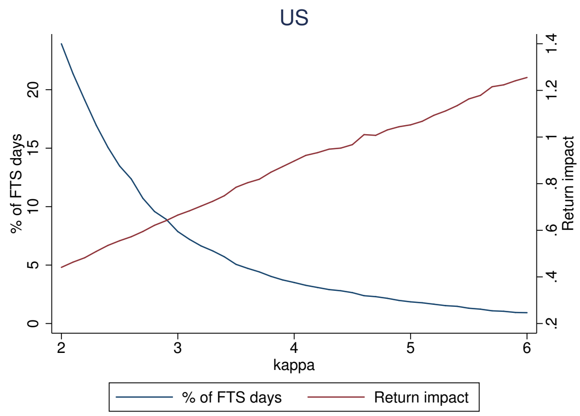
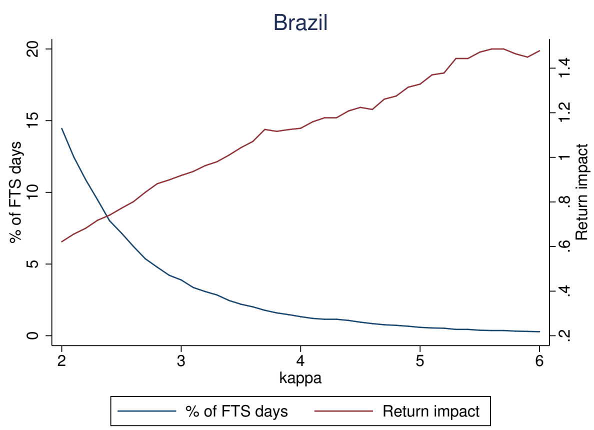
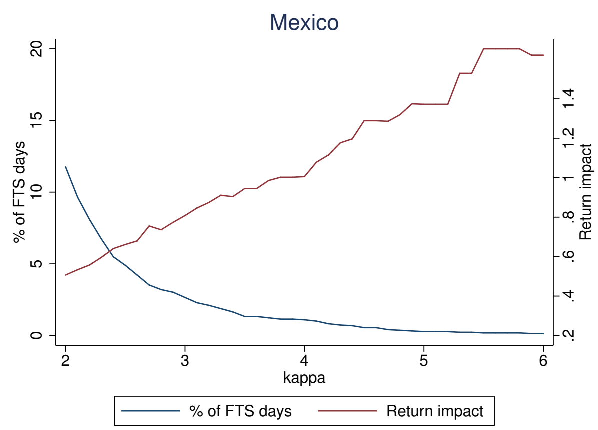


Figure 1: Continued



Panel B: Emerging markets:





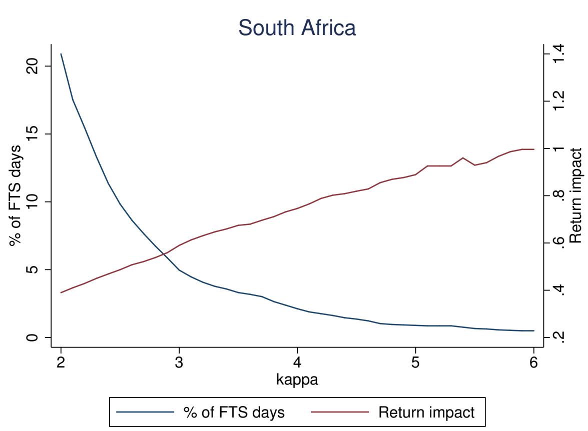


Figure 2: Equity and bond market volatility around FTS events

This figure shows return volatility of equity and bond futures for each country around FTS events. The five-minute interval when FTS occur is denoted as T. The first, second, and third five-minute interval before (after) the FTS interval are denoted as T-1, T-2, T-3 (T+1, T+2, T+3). We calculate the median and inter-quartile of absolute scaled return on equity futures and bond futures for each interval across FTS events. we also plot the unconditional mean over the whole sample as the benchmark.

Panel A: Developed Countries, equity market

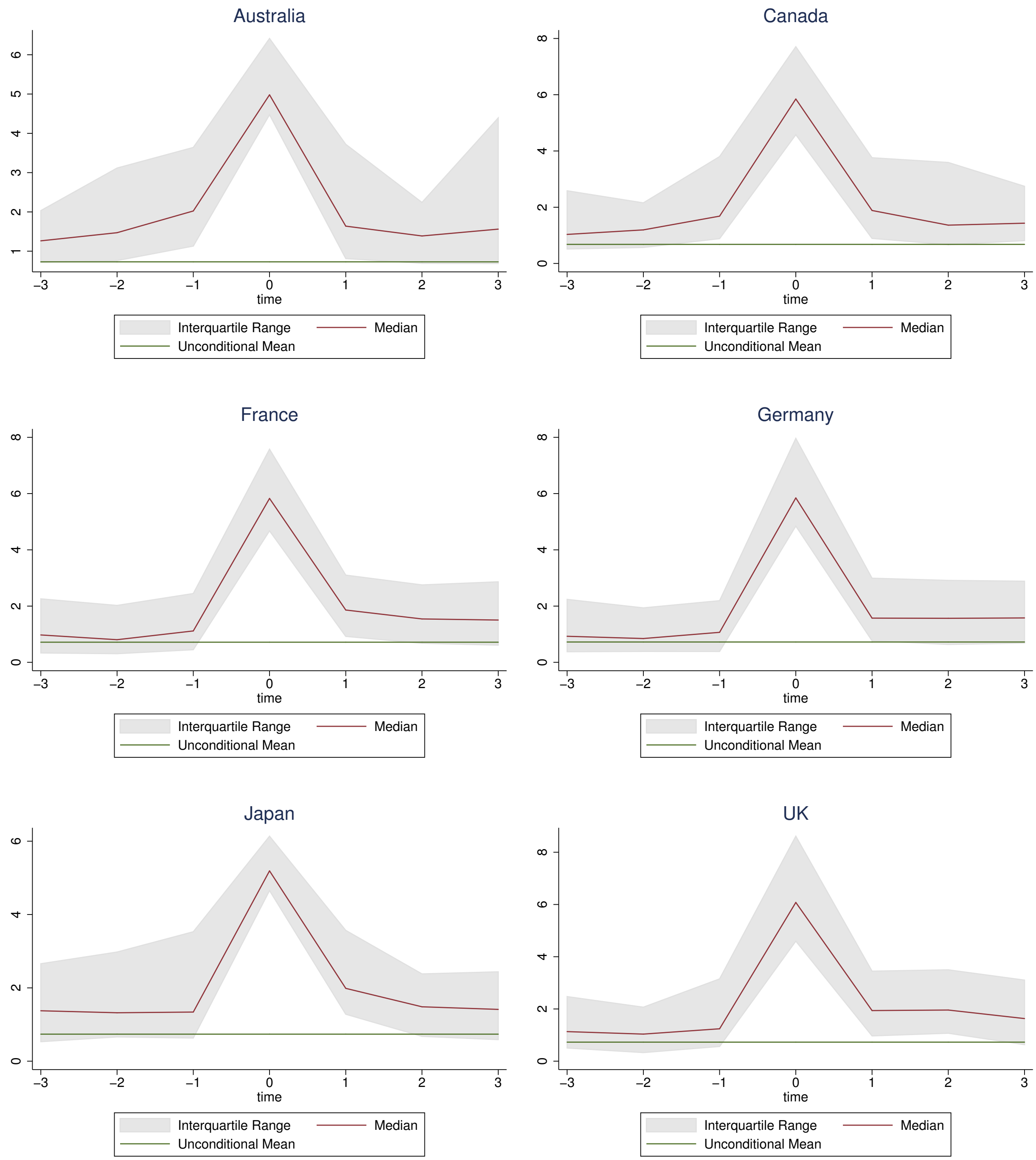
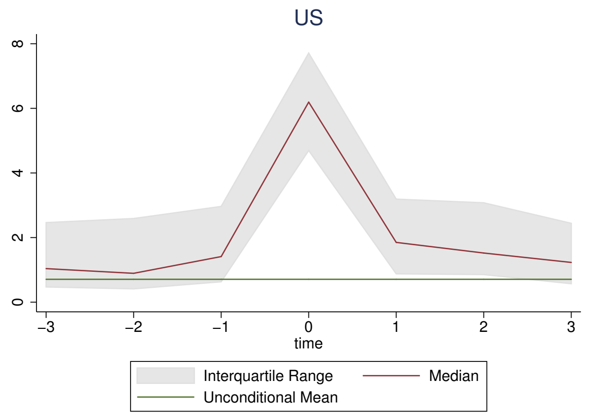
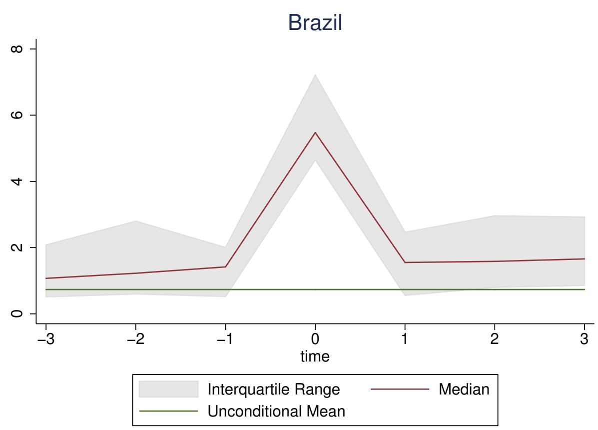
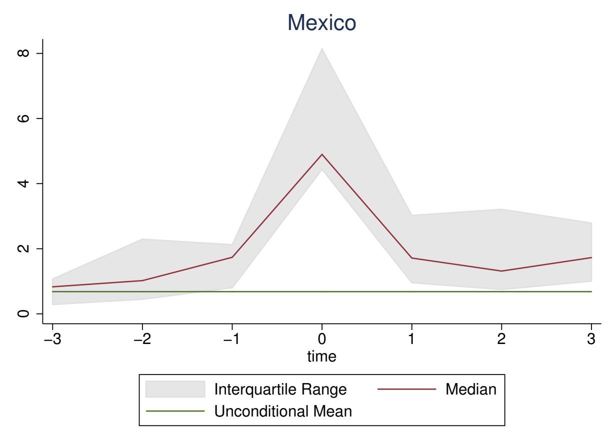


Figure 2: Continued



Panel B: Emerging markets, equity market





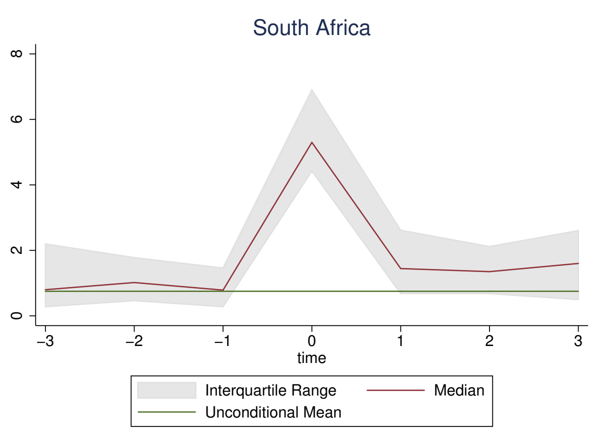


Figure 2: Continued

Panel C: Developed Countries, bond market

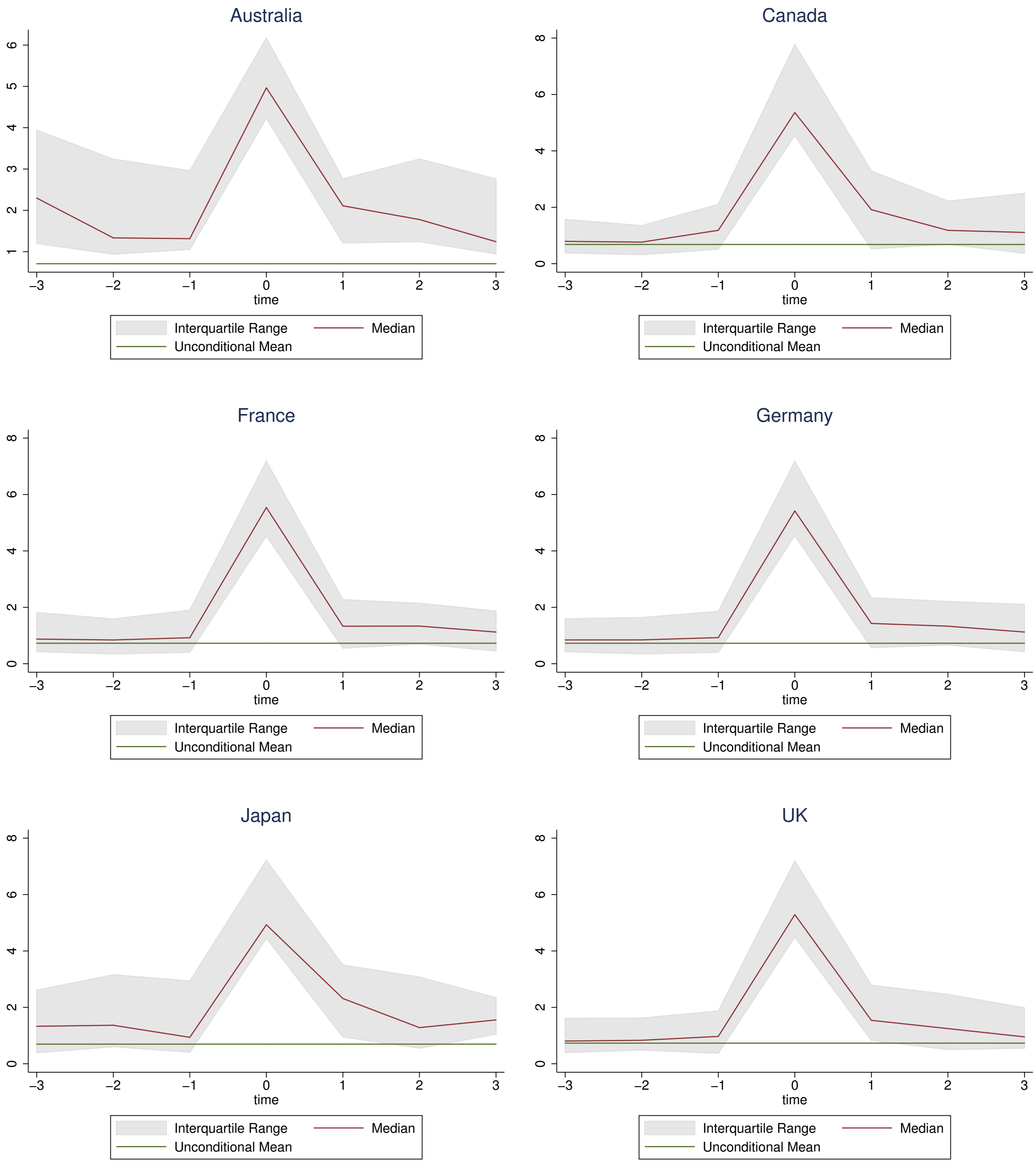
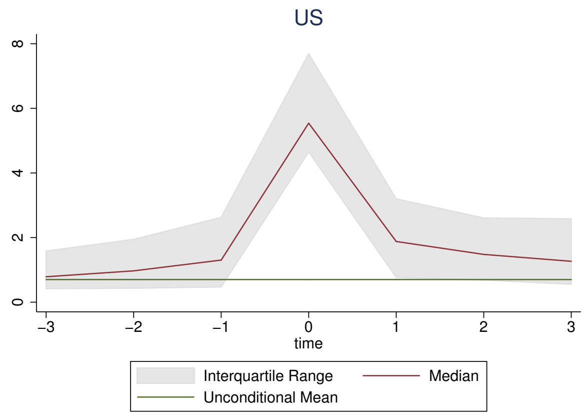
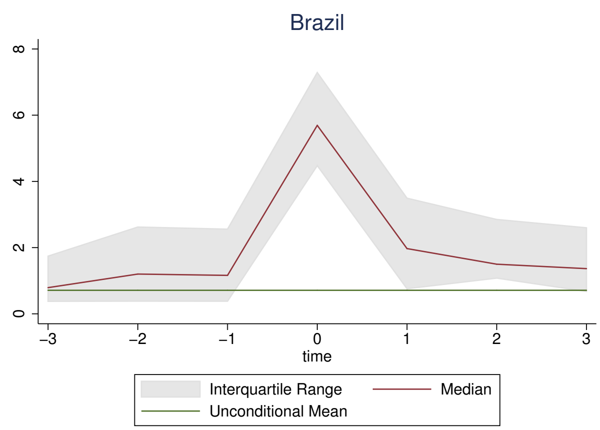
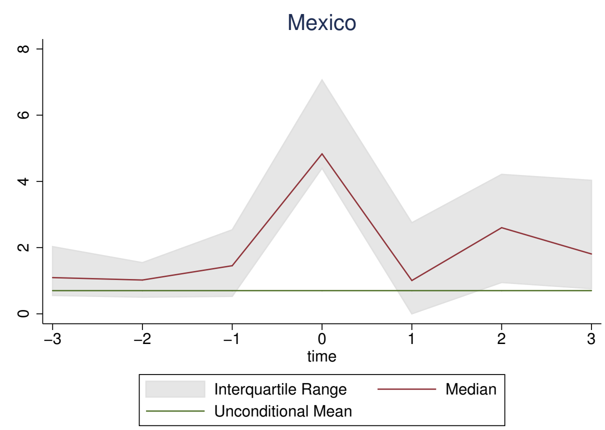


Figure 2: Continued



Panel D: Emerging markets, bond market





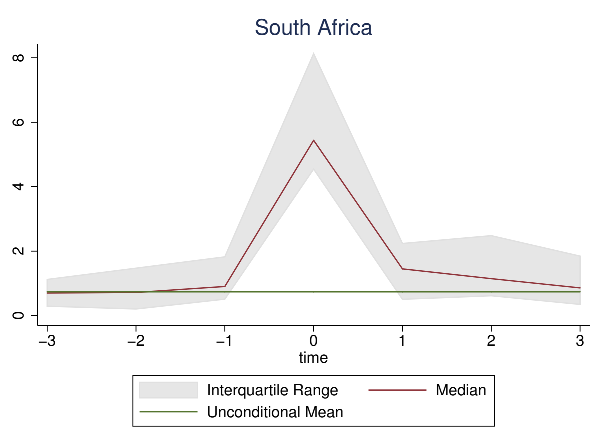


Figure 3: Return impact persistence of FTS events

This figure shows average cumulative returns on equity and bond futures following FTS events. The five-minute interval when FTS occur is denoted as time 0. The t'th five-minute interval after the FTS interval is denoted as time t.

Panel A: Developed Countries

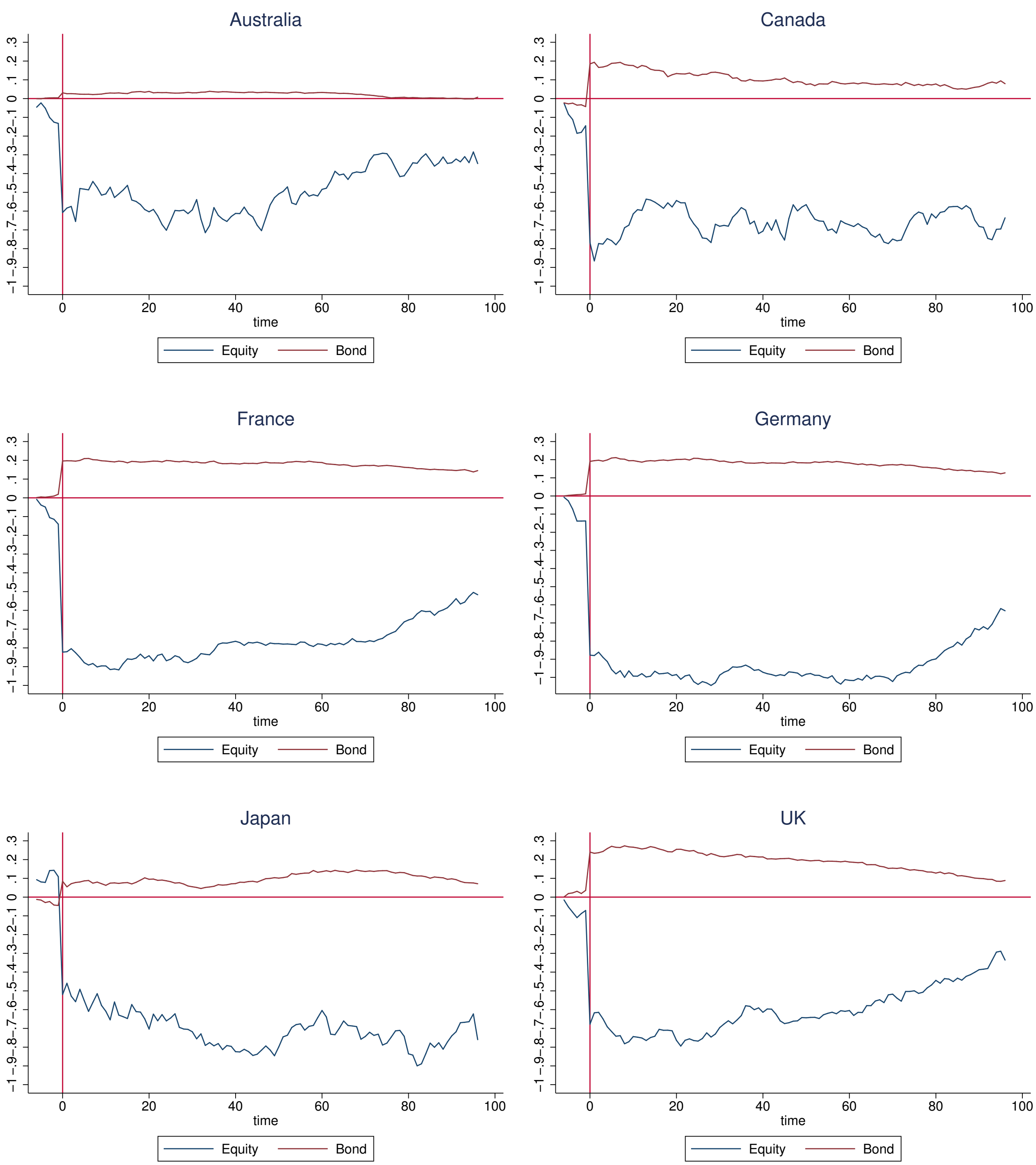
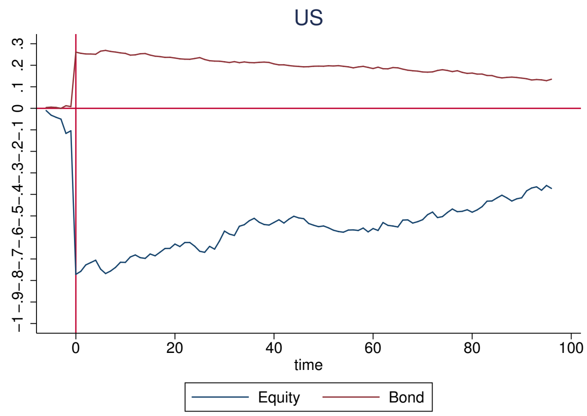
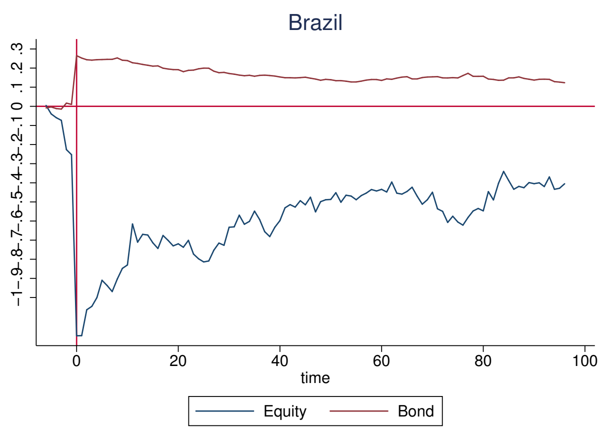
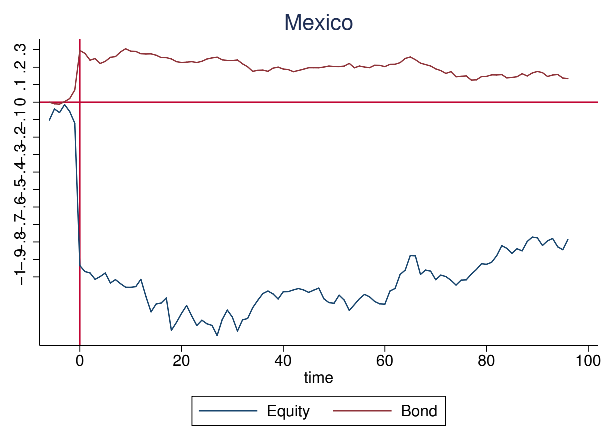


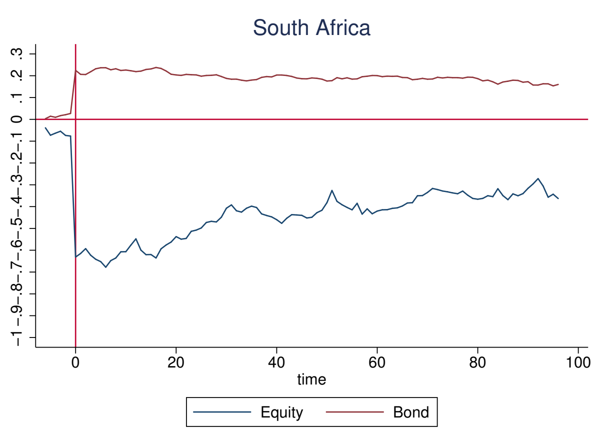
Figure 3: Continued



Panel B: Emerging markets:







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Appendix

Table A.1: Sample Period Contract Month

This table shows the name, the starting and ending date of futures data, and the contract month.

Underlying Instruments	Sample Period	Contract Month
Australia ASX Index	15 Dec 2000 - 11 Aug 2017	After 2010-June contract expired: 3 / 6 / 9 / 12 and the nearest two non-quarterly months. Before 2010-June contract expired: 3 / 6 / 9 / 12
Australian 10 Year Treasury Bond	8 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12
Brazil Bovespa Index	3 Mar 1997 - 11 Aug 2017	Even months.
Canada Ten-Year Government of Canada Bond	3 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12
Canada S&P/TSX 60 Index Standard	8 Sep 1999 - 11 Aug 2017	3 / 6 / 9 / 12
France CAC40 Index	6 Jan 1999 - 11 Aug 2017	3 monthly, 3 quarterly, 8 half-yearly
Germany DAX	8 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12
Germany Euro-Bund	16 Feb 1999 - 11 Aug 2017	3 / 6 / 9 / 12
Japan Nikkei 225	8 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12
Japan JGB	8 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12
Mexico IPC	3 Jan 2007 - 11 Aug 2017	3 / 6 / 9 / 12
South Africa FTSE/JSE Top 40 Index	6 Jul 2005 - 11 Aug 2017	3 / 6 / 9 / 12
UK Long Gilt	1 Apr 1996 - 11 Aug 2017	3 / 6 / 9 / 12
UK FTSE100	1 Apr 1996 - 11 Aug 2017	3 / 6 / 9 / 12
US E-mini S&P 500	9 Sep 1997 - 11 Aug 2017	3 / 6 / 9 / 12
US 10-Year T-Note	3 Jan 1996 - 11 Aug 2017	3 / 6 / 9 / 12

Table A.2: Trading Hours

Futures	Trading hour	Sampled trading hour	Cash Trading hours	Time zone
Australia ASX Index Futures Australian 10 Year Treasury Bond Futures	9:50 to 16:30 8:30 to 16:30	10:00 to 16:00	S&P/ASX 200 10:00 to 16:00	Sydney time
Brazil Bovespa Index Futures	09:00 to 17:55	09:00 to 17:00	IBOVESPA 10:00 to 17:00	Brasília time
Canada S&P/TSX 60 Index Futures Canada Ten-Year Government of Canada Bond Futures	6:00 to 16:15 6:00 to 16:30	8:00 to 16:00	S&P/TSX 60 Index 9:30 to 16:00	Eastern Time
France CAC40 Index Futures	07:00 - 18:30	9:00 to 17:30	CAC 40 9:00 to 17:30	CET
Germany DAX futures Germany Euro-Bund Futures	07:50 to 22:00 08:00 to 22:00	9:00 to 17:30	DAX 9:00 to 17:30	CET
Japan Nikkei 225 Futures Japan JGB Futures	8:45-15:15 8:45-15:00	9:00 to 15:00	Nikkei 225 9:00 to 15:00	Tokyo Time
Mexico IPC Futures	7:30 to 15:00	7:30 to 15:00	S&P/BMV IPC 8:30 to 15:00	Mexico City Time
South Africa FTSE/JSE Top 40 Index Future	8:30 to 17:30	9:00 to 17:00	FTSE/JSE Top 40 Index 9:00 to 17:00	South African Time
FTSE 100 Index Futures UK Long Gilt Futures	1:00 to 21:00 8:00 to 18:00	8:00 to 16:30	FTSE 100 8:00 to 16:30	London Time
US E-mini S&P 500 US 10-Year T-Note Futures	Except 16:15 to 16:30 Except 17:00 to 18:00	8:00 to 16:00	S&P 500 9:30 to 16:00	New York Time

Table A.3: Macroeconomic News Announcements

Category	Announcement	Frequency	Time	Source
Income	GDP Advance	Quarterly	8:30	BEA
	GDP Preliminary	Quarterly	8:30	BEA
	GDP Final	Quarterly	8:30	BEA
	Personal Income	Monthly	8:30	BEA
Employment	Initial Jobless Claims	Monthly	8:30	ETA
	Employment Situation	Monthly	8:30	BLS
Industrial Activity	Industrial Production & Capacity Utilization	Monthly	9:15	FRB
	Factory Orders	Monthly	10:00	BC
	Construction Spending	Monthly	10:00	BC
	Durable Goods Orders	Monthly	8:30	BC
	Business Inventory	Monthly	8:30	BC
Consumption	Advance Retail Sales	Monthly	8:30	BC
	Consumer Credit	Monthly	15:00	FRB
	Personal Consumption	Monthly	8:30	BEA
Housing Sector	Building Permits & Housing Starts	Monthly	8:30	BC
	New Home Sales	Monthly	10:00	BC
Net Exports	Trade Balance	Monthly	8:30	BEA
Government	Government Budget	Monthly	14:00	USDT
Inflation	CPI	Monthly	8:30	BLS
	PPI	Monthly	8:30	BLS
Forward-looking Index	UM Consumer Sentiment Pre	Monthly	9:55	TR/UM
	UM Consumer Sentiment Final	Monthly	9:55	TR/UM
	Consumer Confidence Index	Monthly	10:00	CB
	Index of Leading Indices	Monthly	10:00	CB
	ISM Manufacturing Index	Monthly	10:00	ISM
	ISM Non-manufacturing Index	Monthly	10:00	ISM
Monetary Policy	FOMC Announcement	8 times a year		FED